Bad News Herding, Excessive Write-offs, and Reversals of Restructuring Charges

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Abstract

This paper demonstrates that bad news herding is actually accompanied by bad news over-reporting. By focusing on write-offs during two major recessions of 2001 and 2008 and taking advantage of a unique hand-collected dataset on reversals of restructuring charges, we document that when firms herd in their negative reports, they *over*-state bad news, creating a cushion that can be reversed in the future. Specifically, we show that: (1) large write-offs by early firms are followed by clustered write-offs by their peer firms; (2) herding firms *over*-report and subsequently partially reverse their write-offs; and (3) the reversals help herding firms to meet financial analysts' earnings forecasts that otherwise would not be met. Taken together, these results lend credence to the following mechanism behind bad news herding: firms strategically engage in herding with excessive bad news reports to benefit from subsequent reversals.

Keywords: Big Bath, Herding, Write-offs, Restructuring Charges, Reversals of Restructuring Charges.

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1. Introduction

> "*If you are a smart CEO, you're going to write off everything and then some, maybe even to below-market prices, because you're going to be hidden in the woodshed with everybody else*" (*Wall Street Journal*, October 4, 2007 "Are Banks' Charges Result of Honest Tack, Or "Big Bath" Strategy?")

Managers are often influenced by other firms' actions when making their own decisions. The phenomenon of herding has been documented in many types of business decisions, such as analysts' earnings forecasts, institutional investors' trades, product choices in online marketplaces, and lending decisions.[1] In the financial reporting setting, a growing number of studies finds that firms engage in bad news herding by clustering negative announcements, such as earnings warnings, restatements, and failures to meet analyst forecasts (Tse and Tucker 2010; Myers, Scholz, and Sharp 2013; Bratten, Payne, and Thomas et al. 2016). While prior studies imply that herding is a beneficial strategy for firms because it helps reduce the blame for a negative event, literature does not empirically investigate the mechanism behind negative news herding and the gains that this strategy can bring.

In this paper, we show that firms can benefit from bad news herding by over-stating bad news, which creates reserves to be exploited in the future. Focusing on write-offs during recessions and taking advantage of a unique hand-collected dataset on reversals of restructuring charges, we document that when firms herd in their negative reports, they in fact take the opportunity to *over*state bad news, creating a cushion that can be reversed in the future. Specifically, we show that: (1) during economic downturns, large write-offs by early firms are followed by clustered write-offs by their peer firms; (2) the herding firms *over*-report (engage in

[1] See Trueman (1994), Hong, Kubik, and Solomon (2000), Welch (2000), and Clement and Tse (2005), Wermers (1999), Sias (2004), and Brown, Wei, and Wermers (2013), Huang and Chen (2006), Herzenstein, Dholakia, and Andrew (2011), as well as Zhang and Liu (2012).

a "big bath"[2]) and subsequently partially reverse their write-offs; and (3) the reversals help herding firms meet financial analysts' earnings forecasts. Taken together, these results lend credence to the following mechanism behind bad news herding: firms strategically engage in herding with excessive bad news reports to benefit from subsequent reversals.

The key friction enabling this strategic behavior is the asymmetric market response to initial announced write-offs compared to the following clustered write-offs. Several factors documented in psychology and behavioral finance literature demonstrate decreased market response to clustered news than to standalone news. First, concurrent announcements lead to investor *distraction*, lowering investor attention and muting the market response (Hirshleifer, Lim, and Teoh 2009). Second, *contrast effects* cause bad news to be perceived as less negative when it follows other bad news. Empirical literature documents contrast effects in individuals' perceptions of domains ranging from crime (Pepitone and DiNubile 1976) and attractiveness (Kenrick and Gutierres 1980) to earnings reports (Hartzmark and Shue 2017). Finally, *covariation theory* posits that correlated outcomes across different entities are less likely to be attributed to individual entities than standalone outcomes (Kelley 1967; Koonce and Mercer 2005). In our setting, covariation theory predicts that investors draw less inference about individual firms from clustered announcements. These channels suggest that the market reaction to write-offs issued during an economy- or industry-wide downturn, after other firms have already reported negative news, will induce a milder reaction. By contrast, subsequent performance improvement helped by the reversals of excessive write-offs, occurring as standalone pieces of news, will prompt a more sizable positive response.

[2] "Big bath" has become a general term that describes a large asset write-down or other non-recurring charge strategically taken by a management team that makes the current period's poor results look even worse, but enables reporting better future earnings.

We test our proposed mechanism of big bath herding in the setting of the two most recent recessions recorded by the National Bureau of Economic Research (NBER): the 2001 recession induced by the dot-com crash and the 2008 recession induced by the financial markets meltdown.[3] This setting presents negative economy- or industry-wide shocks that affect a group of firms. Generally Accepted Accounting Principles (GAAP) require firms, whose losses exceed a materiality threshold, to disclose their losses immediately.[4] After the most severely affected firms (Leaders) report write-offs, behavioral factors (distraction, contrast effects, and covariation theory) point towards the market's decreased sensitivity to subsequent bad news reports. As a result, the less severely impacted firms (Followers) might choose to accelerate bad news disclosure and write-off devaluated assets even when these write-offs could be delayed. More importantly, given the market's reduced sensitivity to reported write-offs, it becomes optimal for Followers to undertake a big bath and *over*-report bad news, writing down assets below their fair value if such excessive write-offs can be exploited in the future.[5] It is important to note that the factors muting the market response to Followers' reports do not apply to the early reports of the Leaders, since the first firms to report do not benefit from distraction, contrast effects, or covariation. Thus, firms with material losses, which are required to report their losses immediately, face no incentive to engage in excessive write-offs. Empirically, for each recession, we classify firms into Leaders and Followers based on the timing of their write-offs. We define

[3] The Business Cycle Dating Committee of the NBER maintains a chronology of the U.S. business cycles, which is comprised of alternating dates of peaks and troughs in economic activity. A recession is defined as a period between a peak and a trough, lasting from a few months to more than a year, when a significant decline in economic activity is observed. The recession of 2001 spans from March 2001 to November of 2001, while the recession of 2008 spans from December 2007 to June 2009.

[4] GAAP requires firms to write-down most non-financial assets when their fair values drop sufficiently below their carrying values, but generally does not allow firms to write-up assets when the fair values rise. Write-downs reduce a firm's stock price (Francis, Hanna, and Vincent 1996), providing incentives to delay such disclosure (Dye 1990; Dye and Sridhar 1995; Shin 2003). However, if the reduction in asset value is material enough, managers must disclose bad news to comply with GAAP and avoid potential litigation (Kothari, Li, and Short 2009).

[5] For example, a big bath can allow a firm to smooth earnings in later periods (Kirschenheiter and Melumad 2002) or to meet analysts' forecasts (Moehrle 2002).

"Leaders" as firms that make write-offs around the beginning of the recession, and "Followers" as firms that make write-offs during the subsequent periods.

We confirm our prediction that Followers time their write-offs to occur soon after their peers' write-offs by showing that the probability of a Follower's disclosure at a specific time is positively associated with the number of peer write-offs in the preceding three months.[6]Next, we find evidence of the proposed muted response to Followers' reports: while Leaders' stock prices decline with their write-offs, Followers' stock prices are not sensitive to their reports. This suggests a strategic motive for the Followers' herding reports.

We present three pieces of evidence pointing to Followers' strategic behavior of taking advantage of the reduced stock price sensitivity by engaging in excessive write-offs of their assets. First, we consider Leaders' and Followers' post-disclosure performance. If Followers indeed excessively write-off assets by shifting their future accrued expenses into the current reporting period, then we expect that, compared to Leaders, Followers will report a higher future bottom-line income, which includes all accrual accounting items such as depreciation and amortization as well as other non-operating expenses. By contrast, Followers' operating cash flows should be indistinguishable from those of Leaders, because the cash flow measure is accrual free. Consistent with the excessiveness of Followers' write-offs, we find that Followers report a greater increase in future industry-adjusted median returns on assets (ROA) than Leaders, while showing no difference in future operating cash flows. Second, consistent with the big bath strategy, which allows managers to utilize reserves created by excessive non-recurring charges (Moehrle 2002), we find that Followers are more likely than Leaders to meet/beat analyst earnings forecasts during the two years after the write-offs.

[6] As a robustness, we also checked whether the probability of Followers' disclosure is positively associated with the number of peer write-offs in the preceding six month and obtained qualitatively similar results.

Finally, to provide direct evidence that the Followers' write-offs are both excessive and strategic (yielding a future benefit), we use hand-collected data on reversals of restructuring charges from the 10-K reports of all Leaders and Followers for the write-off year and two years thereafter. Our comprehensive data collection process (detailed in the Appendix), which involves reading firms' notes to financial statements rather than simply mechanically searching for terms such as "reversal", enables us to analyze the complete set of reversals of restructuring charges for all firms in our sample. We show that during the two-year period after the write-off, Followers reverse restructuring charges significantly more frequently than Leaders. More importantly, these reversals tend to coincide with Followers' meeting analyst forecasts that would otherwise not be met, indicating an immediate benefit of the reversals. Overall, our empirical results support the mechanism of big bath herding arising as an optimal strategy for firms who take advantage of the clustered negative news to create reserves for future use.

Our study makes three contributions to the extant literature. First, we contribute to the growing managerial herding literature by demonstrating that firms strategically over-report bad news. While prior studies theoretically (Acharya, DeMarzo, and Kremer 2011) and empirically (Tse and Tucker 2009; Bratten et al. 2016) show that the release of negative information tends to be clustered because firms strategically time the release of information, the strategic *over-reporting* of negative information has not been discussed or documented. Our finding of strategic over-reporting of unfavorable information can be further applied to a variety of events such as accounting restatements, earnings warnings, and missing various accounting benchmarks.

Second, we address an important unanswered question: why do firms herd, what kind of real costs do they save, and what real benefits do they gain by herding? While the existing literature offers some conjectures about why firms herd, such as to reduce blame for earnings

warnings or restatements, it does not present empirical evidence of real benefits associated with herding. Our paper demonstrates that firms benefit from herding by first over-stating bad news and later reversing discretionary charges to report better future performance, since the excessive reporting of bad news in a cluster induces a more mild negative stock price reaction. We use a unique and comprehensive sample of reversals of restructuring charges to demonstrate that clustered write-offs are associated with a higher frequency of future strategic reversals, which help meet analysts' benchmarks that otherwise would not be met.

Third, this paper provides a multi-firm perspective on big bath reporting behavior, therefore extending the scope of prior research, which mainly considers big bath behavior from the perspective of a standalone firm (Moore 1973, Healy 1985, Strong and Meyer 1987, Francis et al. 1996, Kirschenheiter and Melumad 2002, Riedl 2004, Dechow and Ge 2006). We provide new empirical evidence of big bath herding and demonstrate that the big bath strategy can arise as an optimal response to other firms' reporting choices, i.e., it can have a multi-firm nature.

The rest of the paper is organized as follows. Section 2 outlines the empirical hypotheses. Section 3 describes the data. Section 4 presents our research methodology. Section 5 describes our empirical results, and Section 6 concludes the paper.

2. Prior research and hypothesis development

Our study is motivated by the academic literature's interest in managers' financial reporting decisions of negative news. Most prior literature on disclosure suggests that firms tend to delay the release of bad news when negative events happen in isolation (Dye 1990; Dye and Sridhar 1995; Genotte and Trueman 1996). However, Acharya et al. (2011) present a model showing that when a negative economic shock affects the entire economy or industry, firms choose to

promptly release their bad news. This immediate release of bad news leads to clustered reporting in bad times. While the clustered reporting of bad news is not surprising, as firms' performance is correlated and affected by market and industry conditions, Acharya et al. underscore the *strategic nature of timing* of bad news announcements. They also show that, in contrast, good news does not exhibit clustering.

Analytical predictions in Acharya et al. (2011) are supported by recent empirical studies. Tse and Tucker (2010) examine earnings warnings using duration analysis and find evidence of warning clustering, suggesting that managers herd and time their warnings to occur soon after their peers' warnings. They hypothesize that managers time their warnings to cluster with their peers to reduce their apparent responsibility when other firms also issue bad news. Myers et al. (2013) extend the bad news clustering literature by showing that industry peers influence firms' decisions to disclose restatement news in Form 8-K filings, rather than in amended or periodic filings to the Securities and Exchange Commission. Bratten et al. (2016) examine how the reported performance of a leader (defined as a larger firm within an industry that is the first to announce earnings) affects the discretionary reporting of followers (the remaining firms in the same industry that announce earnings after the leader). They find evidence that if a leader falls short of the earnings forecast from financial analysts forecast, followers report lower discretionary accruals and are more likely to miss analysts' expectations as well. Such reporting behavior is consistent with bad news herding, where followers strategically use discretion to flock with the leader when the leader reports bad news. Evidence of good news herding, where followers are more likely to use discretion and meet analysts' expectations when the leader reports good news, are more limited, which is consistent with Acharya et al. (2011), who predict bad news herding, but not good news herding.

While the above papers document bad news herding in different settings, they *assume* that managers herd to reduce personal responsibility or to gain future benefits. However, they do not *provide evidence* that managers indeed *succeed* in achieving these goals. Our main motivation is to take the next step in understanding the mechanism behind bad news herding and the benefits this strategy can bring. Focusing on firms' write-offs decisions during recessions, we simultaneously address three research questions: 1) Do firms herd and strategically time their write-offs to occur soon after their peer firms' write-offs? 2) Do herding firms undertake a big bath by over-reporting their write-offs? 3) Do firms gain future benefits from big bath herding?

Write-offs provide an interesting and meaningful setting for studying managerial strategic timing for three reasons. First, write-offs are significant and highly visible. Second, current accounting rules create a semi-mandatory reporting environment. On the one hand, GAAP stipulates that firms must write-down most non-financial assets when their fair values drop sufficiently below their carrying values. On the other hand, managers exercise significant discretion over the timing and the extent of write-offs because of the subjectivity of fair value determination and auditors' and regulators' difficulty in verifying fair value estimates. Third, excessive write-offs efficiently transfer future expenses into the current period and create accounting reserves, which can be released in future periods to report better performance. These future benefits of created reserves provide managers with incentives to engage in excessive write-offs. Thus, in addition to strategic timing of write-offs as theoretically predicted by Acharya et al. (2011), write-offs facilitate an investigation of whether and why firms engage in strategic over-reporting of bad news.

Our first task is to establish whether bad news herding is applicable to large write-offs reporting. Bad news herding is supported by the rational information transfer as well as

behavioral biases documented in psychology and behavioral finance. From the information transfer perspective, Acharya et al. (2011) predict that an external event, such as peers' write-offs in our setting, may reduce investors' estimate of a firm's earnings. This lowers the equilibrium disclosure threshold causing the immediate release of some previously withheld bad news, resulting in clustering. From the behavioral perspective, *covariation theory* and *contrast effects* also point towards incentives to cluster bad news disclosures. The *covariation theory* predicts that evaluators attribute the agent's behavior to external factors when other agents exhibit similar behavior (Koonce and Mercer, 2005). Since managers are concerned with investors' perception of their ability, they have incentives to minimize their responsibility for write-offs by herding with other firms. For example, motivated by the covariation theory, Tse and Tucker (2010) document that managers herd in earnings warnings to minimize their apparent responsibility for earnings shortfalls. Additionally, the *contrast effects* theory shows people often interpret information by contrasting it with what they have observed recently. Psychologists provide extensive evidence of contrast effect biases ranging from the interpretations of physical dimensions such as weight, length of lines, and shape (Heintz 1950; Sherif, Taub, and Hovland 1958; Krantz and Campbell 1961) and social attributes such as personality impressions (Simpson and Ostrom 1976), criminal acts (Pepitone and DiNubile 1976), and physical attractiveness (Kenrick and Gutierres 1980), to earnings announcements (Hartzmark and Shue 2017). For example, Hartzmark and Shue (2017) present evidence that contrast effects can distort prices in sophisticated and liquid market. They find that investors mistakenly perceive earnings news today as more impressive if yesterday's earnings surprise was bad and less impressive if yesterday's surprise was good, and demonstrate that contrast effects cannot be explained by the information transfer. In our setting, contrast effects theory predicts that if managers are

concerned with the market reaction on the reported bad news, they would be inclined to report their write-offs immediately following peers' write-offs to minimize the market's negative response. Collectively, information transfer and social-phycology channels suggest that after observing Leaders' reporting write-offs Followers will accelerate the timing of their write-offs. Therefore, our first hypothesis predicts:

> **Hypothesis 1:** *A Follower's likelihood of reporting write-offs increases with the number of peer firms that have reported write-offs in the previous periods.*

Next, we establish a link between the market reactions to clustered news (Followers' reports) vs. standalone news (Leaders' report). Several features of human behavior documented in social psychology and behavioral finance explain a lowered market response to clustered news. First, concurrent announcements create investor *distraction*, which leads to muted market reactions. For example, Hirshleifer et al. (2009) document the effect of distraction when multiple firms release their earnings announcements contemporaneously. Investors' distraction is extensively documented in various settings such as Friday earnings announcements (DellaVigna and Pollet 2009), March Madness (Drake, Gee, and Thornock 2015), and competing earnings announcements (Frederickson and Zolotoy 2016), among many others. In our setting, distraction predicts muted market responses to the Follower' negative reports, which are issued in clusters. Second, when a piece of bad news follows other bad news, it is perceived as less negative due to *contrast effects* (Pepitone and DiNubile 1976; Kenrick and Gutierres 1980; Hartzmark and Shue 2017). In our setting, contrast effects predict that Followers' bad news is perceived as less negative when juxtaposed with bad news reported by Leaders. Third, the *covariation theory* posits that multiple similar outcomes across different entities are less likely to be attributed to individual entities than standalone outcomes (Kelley 1967; Koonce and Mercer 2005). In our setting, covariation theory predicts that investors draw less inference about Follower firms from

their clustered announcements. These features of human behavior allude to a muted market reaction to clustered write-offs compared to standalone write-offs. Therefore, we expect different stock price sensitivity to write-offs reported by Leaders and Followers and state our second empirical hypothesis in the following form:

> **Hypothesis 2:** *Stock prices are less sensitive to the magnitude of Followers' write-offs than to those of Leaders.*

An asymmetric price reaction to Leaders' standalone write-offs and Followers' clustered write-offs enables Followers to exploit the muted market response to their write-offs by engaging in excessive write-offs and create accounting reserves. These accounting reserves can be used in the future to report better performance. In contrast, the high sensitivity of stock prices to standalone write-offs discourages Leaders from reporting excessive write-offs, as any additional amount of write-off would result in significantly lower stock prices. Ideally, to test the excessiveness of Followers' write-offs, we would measure the "normal" and "excessive" portions of write-offs. However, difficulty in reliably measuring changes in the fundamental asset values, especially during negative economic shocks, would introduce noise into any proposed expectation model. To overcome this limitation, we contrast post write-off performance of Followers, who report excessive write-offs as they take advantage of a muted market reaction on clustered reports, to Leaders, who report proper write-offs because of the strong negative market reaction to their standalone write-offs. Specifically, first, as an indirect test, we examine post write-off earnings and cash flows of Leaders and Followers. Next, as a direct test, we analyze the reversals of restructuring charges.

Thus, our third set of empirical hypotheses follows from the differential impact of the excessive and proper write-offs on firms' future accounting reporting. By reporting an excessive write-off, a firm efficiently shifts its future expenses into the current period (Elliott and Hanna

1996, Burgstahler, Jiambalvo, and Shevlin 2002, Dechow and Ge 2006). Confirming this, the literature finds a positive association between negative special items and future performance, attributing this - at least partially - to the accelerated and excessive expense recognition (Moehrle 2002; Atiase, Platt and Tse 2004; Cready, Lopez, and Sisneros 2012). Alternatively, an improvement in future performance can be caused by real business decisions. To distinguish between these explanations, literature uses accounting measures with varying reliance on accruals (Atiase et al. 2004, Cready et al. 2012). For example, while bottom-line GAAP income, which includes all accrual accounting items, will reflect the release of accounting reserves, operating cash flows, which are accrual free, will not be affected by the expense shifting. We use this feature of accrual earnings and cash flows to differentiate between truthful and excessive write-offs of Leaders and Followers. Ceteris paribus, if Followers shift future expenses by overstating their write-offs, their future operating performance measured by bottom-line accounting earnings will be higher than that of the Leaders, while their future cash flows will not be different from those of the Leaders. This reasoning leads to our third set of empirical hypotheses:

> **Hypothesis 3a:** *Followers experience better future performance as measured by bottom-line GAAP accounting earnings than do Leaders.*
>
> **Hypothesis 3b:** *Followers' future performance as measured by operating cash flows is not different from that of Leaders.*

While different post write-off performance of Leaders and Followers provides indirect evidence of the excessiveness of Followers' write-offs, analysis of post-write-offs reversals of restructuring charges would provide more direct evidence. Restructuring is a "program that is planned and controlled by management, and materially changes either the scope of a business undertaken by an entity, or the manner in which that business is conducted, as defined by the

International Accounting Standard No. 37 in 2002" (ASC 420-10-20). While restructuring charges are a result of a firm's overall investment strategy, managers still have substantial discretion regarding the amount and timing of restructuring charges, because restructuring charges usually include estimates of future costs, which can be ambiguous. If a firm overstates restructuring charges, it creates hidden balance sheet reserves that can be reversed in the future periods to increase future earnings. Moehrle (2002) demonstrates that companies reverse a portion of restructuring charge accruals in future quarters in order to beat analysts' earnings forecasts or avoid reporting net losses. Detailed examination of restructuring charge reversals enables a direct test of managers' use of excessive restructuring charges to enhance future earnings. Such a test is based on an observable transaction (i.e., a restructuring charge reversal) rather than on noisy estimates of earnings management (i.e., discretionary accruals). If Followers take excessive write-offs to utilize them in future periods, we expect to find more evidence of reversals of restructuring charges for Followers than for Leaders. Therefore, we state our fourth hypothesis in the following form:

> **Hypothesis 4:** *Followers reverse restructuring charges more frequently than Leaders in the period following the write-off.*

Prior studies suggest that meeting analyst forecasts is among the most important incentives for managing earnings (Skinner and Sloan 2002; Richardson, Teoh, and Wysocki 2004). A release of reserves created by excessive write-offs, such as a reversal of prior restructuring charges, helps meet earnings targets (Moehrle 2002). Therefore, if Followers indeed take a big bath by shifting future period expenses to the current period write-offs, we expect that Followers will have a higher likelihood of meeting analysts' expectations compared to Leaders in the periods after the write-offs. Furthermore, the release of accounting reserves created by the excessive write-offs can help meet earnings benchmarks when these benchmarks

otherwise would not be met. Therefore, if Followers report excessive write-offs, we expect that reversals of restructuring charges helps Followers meet analysts' earnings benchmarks more often than Leaders. Thus, we state our fifth hypothesis in the following form:

> **Hypothesis 5:** *Followers' reversals of restructuring charges are associated with higher probability of meeting analysts' forecasts in periods following the write-offs than that of Leaders.*

3. Sample selection and descriptive statistics

We use two major negative economic shocks that have affected a wide range of industries — the 2001 recession of the dot-com crash and the 2008 recession associated with the financial crisis — to test our empirical hypotheses. NBER's Business Cycle Dating Committee maintains a chronology of the U.S. business cycles.[7] The recession of 2001 lasted from March 2001 to November 2001, while the recession of 2008 lasted from December 2007 to June 2009. These recessions provide a good setting to test our hypothesis because 1) they affected almost all industries in the economy and 2) they were strong enough to trigger write-offs.

Beginning with 2000, COMPUSTAT provides a breakdown of the largely ambiguous category "Special Items" into items related to (i) Acquisition/Merger, (ii) Gain/Loss on Sale of Assets, (iii) Impairment of Goodwill, (iv) Settlement (Litigation/Insurance), (v) Restructuring Costs, (vi) Writedowns, (vii) Extinguishment of Debt, (viii) In-Process Research & Development, and (ix) other Special Items. Managers have differential discretion regarding the timing and amount of different types of special items. For example, managers have little discretion over reporting losses from legal/insurance settlements or extinguishment of debt, because the timing of events that trigger these items is often controlled by an outside party. We believe that write-downs, restructuring charges, and goodwill impairments are best suited for

[7] See announcements from the NBER's Business Cycle Dating Committee: http://www.nber.org/cycles.html.

testing managerial discretion over reporting strategies.[8] We take advantage of the expanded COMPUSTAT reporting on categories of special items and define a write-off event as any quarter observation for which the sum of pre-tax "write-downs" (COMPUSTAT item WDP), "restructuring costs" (COMPUSTAT item RCP), and "impairment of goodwill" (COMPUSTAT item GDWLIP) exceeds one percent of the lagged firm total assets.

The first step in our sample selection is to identify write-off firm-quarter observations that have earnings announcements during the period starting 3 months before and ending 18 months after the beginning of the recession and that have non-missing financial data necessary for our analysis.[9] The starting and ending points of the sample are heuristic and motivated by the observed higher frequency of write-offs during the recession. We chose to start 3 months before the beginning of the recession, as determined by NBER, to capture the reporting of the bellwether industries or firms. Prior literature shows that certain industries or firms that are characterized by high interconnectedness with their direct suppliers/customers and/or indirect chains of downstream sectors may originate aggregate fluctuations from microeconomic shocks (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi 2012; Bonsall, Bozanic, and Fischer 2013; Ahern and Harford 2014; Aobdia, Caskey, and Ozel 2014), and thus these industries/firms may write-off assets even before the beginning of the recession.

[8] The recession of 2001 falls into the transitional period from the long-accepted practice of amortization of goodwill acquired in business combinations under SFAS 121, "Accounting for impairment of long-lived assets", to SFAS 142, "Goodwill and other intangible assets", which instead requires companies to periodically review goodwill for impairment and to recognize a loss if goodwill is impaired. For robustness, we exclude goodwill impairment from our write-off sample, and define a write-off event as any quarter observation for which the sum of pre-tax "write-downs" (COMPUSTAT item WDP), and "restructuring costs" (COMPUSTAT item RCP) exceeds one percent of the lagged firm total assets. All results hold for a sample of write-offs that excludes goodwill impairments.

[9] We require the presence of the following variables: total assets, shareholders' equity, market value of equity, sales, net income, operating cash flows, operating earnings, and CEO's name in the year preceding the write-off year and the write-off year itself, monthly stock returns during the year preceding the write-off, and daily stock returns over [0; +3] days relative to the earnings announcement.

We identified 1118 firm-quarter observations with write-offs in the first step. Second, following prior literature, we eliminate financial firms and firms in gas, oil, and utilities industries because these firms have a different regulatory environment (Francis et al. 1996; Riedl 2004; Haggard, Howe, and Lynch 2015). Specifically, we exclude observations in industries with codes 30 (Petroleum and Natural Gas), 31 (Utilities), 45 (Banking), 46 (Insurance), 47 (Real Estate), 48 (Trading), and 49 (Almost Nothing) of Fama and French's (1993) 49-industry classification and retain 1039 firm-quarter observations.

Third, because our goal is to study how the timing and magnitude of a firm's write-off is affected by its peers, we retain only the first firm-quarter write-off reported during the sample period. Any write-offs that are subsequent to a firm's first write-off might be influenced by its own financial situation and market reaction to its previously announced write-off. After this step, we retain 694 firm-quarter observations.

Fourth, we require that each industry must have at least three write-offs per recession, and we delete 24 events that fail to satisfy this requirement. Fifth, we define a "Leader" as any firm that has a write-off during the period starting 3 months before and ending 3 months after the beginning of the recession and a "Follower" as any firm that has a write-off during our sample period starting 4 months after the beginning of the recession. We excluded industries for which we did not observe write-offs during the Leaders' period ([-3; +3] months relative to the beginning of recession). This brings us to our final "write-off" sample of 589 firms. Table 1 summarizes our sample selection process.

We perform several robustness tests to examine alternative specifications for Leaders and Followers. First, to alleviate concerns that our results are affected by the timing of the fiscal year-end we repeat our analysis on the sample of firms that have only a December fiscal year-

end. Second, we define Leaders as firms with write-offs in the 3-month period after the beginning of the recession, i.e., we exclude pre-recession months. Third, we limit the timing of Followers' write-offs to the one-year period after the Leaders' write-offs. All results hold for these alternative specifications.

Our stock return data comes from the Center for Research in Security Prices' (CRSP) monthly returns database. We extract financial statement data and other company information from the Merged CRSP-COMPUSTAT database and obtain analyst coverage from the I/B/E/S database (both its detailed and summary history files) for each stock in our sample, using historical CUSIP codes to link these two databases. We define the number of analysts covering a stock as the number of unique analysts issuing earnings per share (EPS) forecasts during a calendar year.

We hand-collect the instances of restructuring charge reversals by gathering 10-K reports for all of the companies in our sample for three fiscal years after the event quarter from the Edgar reporting portal of the Securities and Exchange Commission.[10] Out of 589 firms in our sample, we were able to obtain 10-K reports for 583, 576, and 554 firms for the first, second, and third fiscal years after the write-off quarter, respectively. Specifically, we read the sections of the "Notes to Financial Statements" in the 10-K reports that describe the reporting of restructuring activities and record whether a firm fully or partially reversed previously accrued restructuring charges.[11] In Appendix, we provide detailed examples of firms' reporting practices for reversals of restructuring charges.

[10] https://www.sec.gov/edgar/searchedgar/companysearch.html.

[11] We do not use a simple keyword search to find the reversals of restructuring charges, but instead read the corresponding notes to financial statements because firms report reversals in various forms. While firms sometimes use the words "reverse" or "reversal", they often report a negative "change in estimates", or a negative non-cash adjustment to a restructuring accrual account. By actually reading all of the corresponding notes, we are able to 1) collect data on restructuring charge reversals for a larger number of companies and 2) have a more precise data set.

Table 2, Panel A displays the frequency and amount of write-offs by industry and recession. Electronic Equipment, Computer Software, Business Services, and Wholesale industries have the largest numbers of write-offs in the 2001 recession (47, 31, 20, and 20, respectively). Similarly, Electronic Equipment, Business Services, Retail, Wholesale, and Computer Software industries have the most write-offs in the 2008 recession (45, 36, 24, 21, and 21, respectively). The higher frequency of write-offs in these industries might be explained by the relatively greater number of firms operating in them. For most of the industries, the Leader group consists of 1-3 firms.

Table 2, Panel B summarizes the frequency of write-offs relative to the recession peak for all firms in our sample. The first two months after the beginning of the recession have the highest frequency of write-off reporting (45 and 37 observations, respectively). Figure 2 graphically summarizes the frequency of Leaders' and Followers' write-offs relative to the beginning of the recession. Roughly 65% of all write-offs happen during the first year.

We summarize the characteristics of Leaders and Followers in Table 3. Leaders are somewhat larger in size than Followers but have a lower mean book-to-market ratio than Followers, suggesting that large growing firms tend to lead the write-offs triggered by the recession. The median changes in return on assets (ROA) from years -5 to -1 prior to the write-off are significantly more negative for Leaders than for Followers (the median difference is -0.003). This is consistent with our prediction that Leaders' write-offs come in response to the decline in their operating performance, while Followers' write-offs are not driven by their weak performance but rather by strategic timing of the write-offs. Similarly, the mean and median cumulative abnormal returns computed over the year preceding the write-off are significantly more negative for Leaders than for Followers (the mean difference is -0.138, and the median

difference is -0.171). Finally, the return synchronicity, measured as the R^2 of a firm's weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter, is higher for Followers than for Leaders, suggesting that Followers' stock prices are more sensitive to the price movement of their peer firms than that of the Leaders. Overall, from Table 3, we can observe that only Leaders exhibit a significant decline in operating and stock performance in the years before the write-offs, while Followers show no sign of a performance deterioration, but their stock prices are more sensitive to their peers' returns.

4. Methodology

Herding

We use duration analysis to test our empirical Hypothesis 1 that Followers time their write-offs to occur soon after industry peers' write-offs. Specifically, we estimate whether the probability of firm *i* reporting a write-off, given that firm *i* has not reported any write-offs since the beginning of the sample period, is affected by the incidence of its industry peers' write-offs. To test our Hypothesis 1, we use the Cox proportional hazard model in the following specification[12]:

$$h\,(t_i) = h_0(t_i)(a_0 + a_1 Peerwriteoff_i + a_2 UE_i + a_3 \Delta Sale_i + a_4 RET_i + a_5 Size_i + a_6 MKTshare_i + a_7 SynEarn_i + a_8 SynRet_i + e_i) \quad (1)$$

where, dependent variable $h(t_i)$ is the hazard function of a write-off at time *t*. Variable *t* indicates the number of days from the beginning of the recession to the earnings announcement day for the quarter when a firm reports a write-off.[13] The Cox model generalizes a proportional hazard model by allowing the distribution of the baseline hazard function, $h_0(t_i)$, to take any

[12] To insure robustness of our duration analysis, we also use general piecewise log-logistic model as an alternative specification and obtained even stronger results. These results are not tabulated due to a space constrains, but are available upon request.

[13] We consider the write-off to be large if the sum of the write-down, restructuring charges and goodwill impairment (COMPUSTAT items WDP, RCP, and GDWLIP) exceeds one percent of lagged total assets.

form. Our primary variable of interest is $Peerwriteoff_i$, measured as the number of write-offs reported by industry peers in the three-month period preceding firm i's write-off.[14] If a manager's decision to write-off the assets is accelerated by peers' write-offs, the coefficient on $Peerwriteoff_i$ should be positive. Alternatively, if a manager's decision is unrelated to peers' write-offs, the coefficient estimate is expected to be insignificantly different from zero.

We include three sets of control variables that are identified in prior literature as being associated with firms' decisions to write-off assets (Francis et al. 1996, Reidl 2004). The first set of variables captures economic conditions that affect firm *i*'s decision. Specifically, we use the magnitude of pre-write-off unexpected earnings (UE_i), sales growth ($\Delta Sale_i$), and the cumulative abnormal stock return (RET_i). We define UE_i as the difference between the latest outstanding analyst consensus forecast before the earnings announcement and actual earnings, deflated by the firm's stock price at the end of the last fiscal year prior to the event. $\Delta Sale_i$ is the firm's sales growth relative to the same quarter in the previous year. RET_i is the firm's cumulative abnormal return computed for the year preceding the write-off.

The next set of control variables reflects a firm's disclosure environment, litigation concerns, and investors' scrutiny. We include a firm's market capitalization ($Size_i$), measured as a natural logarithm of the firm's market capitalization at the end of the last fiscal year preceding the event, and the market share of the firm's product in the industry ($MKTshare_i$), measured as the ratio of the firm's total sales in the most recent fiscal year before the event to the industry's total sales in that year.

Our final set of control variables accounts for the synchronicity of a firm i's earnings and stock returns with the industry peers, $SynEarn_i$ and $SynRet_i$. Firms with fundamentals that are

[14] We also use an alternative specification, which measures the number of large write-offs by industry peers during the six months preceding firm *i*'s write-off, and obtained similar results.

highly synchronous with those of their industry peers are more likely to be affected by common shocks and thus have a propensity to write-off the assets faster. Following Tse and Tucker (2010) and Morck, Yeung, and Yu (2000), we measure earnings synchronicity ($SynEarn_i$) by the R^2 of the regression of the firm's return on assets (ROA) on the industry ROA (calculated as the total industry earnings divided by the total industry assets) in the 20 quarters before the event quarter. Similarly, we calculate stock return synchronicity ($SynRet_i$) as the R^2 of the regression of the firm's weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter (Piotroski and Roulstone 2004; Tse and Tucker 2010). We convert all continuous control variables into within-industry-quarter ranking because we are interested in examining a firm's disclosure behavior relative to its industry peers. We rank all control variables (UE_i, $\Delta Sale_i$, RET_i, $Size_i$, $MKTshare_i$, $SynEarn_i$, $SynRet_i$) among all firms in the industry quarter that are covered by COMPUSTAT and CRSP.

Price Response to the Write-offs of Leaders and Followers

A majority of firms disclose information about large write-downs, restructuring charges, and goodwill impairment at the earnings announcements (Francis et al. 1996).[15] Thus, we test Hypothesis 2 by regressing stock returns at the time of earnings announcements on the amount of the write-offs, controlling for earnings surprises and other factors that might influence price elasticity. In particular, we run an OLS regression in the following form:

$$\begin{aligned} ANNRET_i = \gamma_0 + \gamma_1 WRITEOFF_i + \gamma_2 Follower_i + \gamma_3 WRITEOFF_i * Follower_i \\ + \gamma_4 UE_i + \gamma_5 Size_i + \gamma_6 BM_i + \gamma_7 SynRet_i + \gamma_8 SynEarn_i + \varepsilon_i \end{aligned} \quad (2)$$

[15] We search Factiva database for earnings announcements and conference calls for each firm in our sample. We confirm that 85% of firms disclosed write-offs at earnings announcements.

where $ANNRET_i$ is firm *i*'s compounded excess return over days [0, +3] relative to the earnings announcement day. Excess return is measured as the difference between the realized return and the corresponding size and book-to-market portfolio of firms in the CRSP-COMPUSTAT universe.[16] $WRITEOFF_i$ is the sum of the write-down, restructuring charges, and goodwill impairment (COMPUSTAT items WDP, RCP, and GPWLIP), converted to positive values, and deflated by the total assets at the end of the last fiscal year prior to the write-off quarter. $Follower_i$ is an indicator variable that equals one if firm *i* is a Follower and zero otherwise. A negative coefficient on $WRITEOFF_i$ would indicate that stock returns at the time of the announcement react negatively to Leaders' write-offs. To capture Followers' and Leaders' differential price sensitivity to write-offs, we interact the size of the write-off, $WRITEOFF_i$, with the $Follower_i$ dummy. A positive coefficient on this interaction term would indicate that stock returns react less negatively per dollar of write-off for Followers than for Leaders.

To control for other information that is contemporaneously announced, we include the earnings surprise adjusted for the write-offs (UE_i). We also control for a firm's market capitalization ($Size_i$), book-to-market ratio at the end of the fiscal year prior to the write-off (BM_i), and a firm's synchronicity of earnings and stock returns with its industry peers, $SynEarn_i$ and $SynRet_i$. The definition of UE_i, $Size_i$, $SynEarn_i$ and $SynRet_i$ is provided in regression 1. Similarly to regression 1, we convert continuous control variables into within-industry-quarter ranking. While UE_i, $Size_i$, BM_i, $SynEarn_i$, $SynRet_i$ are ranked among all firms in the industry quarter that are covered by COMPUSTAT and CRSP, $WRITEOFF_i$ is ranked only among the firms included in our write-off sample.

[16] We obtain daily size and book-to-market benchmark portfolio returns from Professor Kenneth R. French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary.html.

Future Performance of Leaders and Followers

We test empirical Hypotheses 3a and 3b by running the following OLS regression:

$$\begin{aligned}\Delta PERF_{i,t,t+2} = {} & \gamma_0 + \gamma_1 Follower_i + \gamma_2 WRITEOFF_{i,t} + \gamma_3 WRITEOFF_{i,t} * Follower \\ & + \gamma_4 PERF_{i,t} + \gamma_5 \Delta PERF_{i,t-1,t} + \gamma_6 \Delta ROE_{i,t-5,t} + \gamma_7 \Delta BM_{i,t-5,t} \\ & + \gamma_8 \Delta SALE_{i,t-1,t} + +\gamma_9 INDGROWTH_{i,t-5,t} + \gamma_{10} FINLEV_{i,t-1} \\ & + \gamma_{110} SIZE_{i,t} + \gamma_{12} BM_{i,t} + \gamma_{13} MKTShare_{i,t-1} + \gamma_{14} \Delta MGMT_{i,t-1,t} \\ & + \gamma_{15} SynEarn_{i,t} + \gamma_{16} SynRet_{i,t} + \mu_i \end{aligned} \quad (3)$$

where dependent variables ($\Delta PERF_{i,t,t+2}$) measure the change in future performance of firm *i* from the event year *t* to two years after event. We use two performance measures: change in industry-adjusted return on equity ($\Delta ROA_{i,t,t+2}$) and change in operating cash flow ($\Delta CFO_{i,t,t+2}$). We calculate *ROA* as the ratio of income before extraordinary items (COMPUSTAT item IB) to the total assets (COMPUSTAT item AT). We compute *CFO* as the ratio of cash from operations (COMPUSTAT item OANCF) to the total assets. To avoid comparison of the performance metrics across different phases of the economic cycle and to address a possibility that the mean reversion of firms' performance is correlated with the economic cycle, we adjust all performance measures by the industry-year by subtracting the industry median *ROA* or *CFO* for the corresponding year.[17]

Our main variable of interest is $Follower_i$. If Followers make excessive write-offs by shifting future period expenses into the current period, we expect that their future ROA, which encompasses all accrual components, will be higher than that of Leaders, who report write-offs truthfully and thus do not have accrual reserves that help achieve better future accounting performance. Therefore, we expect a positive coefficient on $Follower_i$ when $\Delta ROA_{i,t,t+2}$ is a

[17] We determine industry based on the two-digit SIC codes.

dependent variable. However, we expect that the coefficient on $Follower_i$ is insignificantly different from zero when $\Delta CFO_{i,t,t+2}$ is a dependent variable, because these accounting measures do not contain accrual components that can be used by managers to release reserves created by excessive write-offs.

We include the write-off amount ($WRITEOFF_i$) and the interaction term between $WRITEOFF_i$ and an indicator variable $Follower_i$ in the regression. If indeed the excessive write-off allows Followers to boost their future earnings, we expect a positive coefficient on the interaction term between $WRITEOFF_i$ and $Follower_i$ when dependent variable is $\Delta ROA_{i,t,t+2}$. However, we expect that the coefficient on $WRITEOFF_i * Follower_i$ is insignificantly different from zero when $\Delta CFO_{i,t,t+2}$ is a dependent variable.

We control for firm characteristics that prior literature has shown to be correlated with the change in future performance. In particular, we include the level and the change of the performance measures ($PERF_{i,t}$ and $\Delta PERF_{i,t-1,t}$), where $PERF_{i,t}$is either the industry adjusted ROA or CFO for the event year, and $\Delta PERF_{i,t-1,t}$ is the change in these measures from one year before the event year to the event year. A systematic decline in a firm's performance before the write-off, measured as the mean change in the book-to-market ratio (ΔBM_i) and the return on equity ($\Delta ROE_{i,t-5,t}$) over the five years preceding the event year, might affect the speed of a firm's recovery from a negative economic shock, and thus we include these as control variables. We include a firm's sales growth ($\Delta SALE_{i,t-1,t}$) in the year prior to the event year because a trend in sales growth affects future performance. We include industry growth ($INDGROWTH_i$), which is computed as the mean change in aggregated industry sales over the five years prior to the event year, to control for the effect of the overall industry trend on individual firms. We also include financial leverage ($FINLEV_i$), defined as the ratio of total assets (COMPUSTAT item

TA) to the book value (COMPUSTAT item CEQ) at the end of the last fiscal year prior to the event, and the change in top management ($\Delta MGMT_{i,t-1,t}$), which is defined as an indicator variable that equals one if a firm experiences a change in the top three executives either in the write-off year or in the prior year. Finally, we control for size ($Size_{i,t}$), the book-to-market ratio ($BM_{i,t}$), market share ($MKTShare_{i,t-1}$), and the synchronicity of a firm's earnings and stock returns with its industry peers ($SynEarn_{i,t}$ and $SynRet_{i,t}$), which are defined the same way as in regressions (1) and (2).

Reversals of restructuring charges

To test our Hypothesis 4, which states that Followers reverse restructuring charges more often than Leaders in the years following the write-offs, we employ the following logistic regression:

$$\begin{aligned}\Pr\left(Reverse_{i,N}\right) = F(&\eta_0 + \eta_1 Follower_i + \eta_2 Shortfall_i + \eta_3 WRITEOFF_i + \\ &\eta_4 INST_i + \eta_5 Analyst_i + \eta_6 RD_i + \eta_7 LOSS_i + \eta_8 Size_i + \eta_9 BM_i + \\ &\eta_{10} SynEarn_i + \eta_{11} SynRet_i + \xi_i)\end{aligned} \quad (4)$$

where $Reverse_{i,N}$ is an indicator variable that equals one if firm i reverses restructuring charges in the year N after a write-off, and zero otherwise. We consider two fiscal years after the write-off, and thus N takes values 1 or 2. Our main explanatory variable is $Follower_i$. We expect a positive coefficient on $Follower_i$ if Followers reverse restructuring charge more often than Leaders.

We control for other variables that might influence managerial decisions to partially reverse restructuring charges. Moehrle (2002) shows that firms reverse restructuring charges more frequently when pre-reversal earnings are below analysts' earnings forecasts. Thus, to control for this incentive, we include $Shortfall$, which is an indicator variable that equals one if

a firm's pre-reversal earnings are below consensus analysts' forecasts and zero otherwise. Pre-reversal earnings are computed as actual earnings reported on IBES minus reversal amount multiplied by statutory tax rate of 40 percent. Other control variables are related to a firm's monitoring environment, litigation concerns, investors' scrutiny, and the degree of operating uncertainty. Specifically, we include a firm's market capitalization ($Size_i$), institutional ownership ($INST_i$), which is the percent of a firm's shares outstanding that is held by institutions, number of analysts that follow a firm ($Analyst_i$), and research and development intensity (RD_i), computed as COMPUSTAT item XRD divided by the total assets at the end of the fiscal year before the write-off. R&D intensity serves as a proxy for the firm's reliance on implicit claims with its other stakeholders (e.g., customers, employees, and suppliers) and as an indicator of uncertainty in a firm's future performance. The literature shows that the earnings of loss firms are less value relevant for investors. Thus, we proxy the value relevance of earnings by the indicator variable $LOSS_i$, which equals one if firm i reports a negative income before extraordinary items (COMPUSTAT item IB) in the fiscal year before the event and zero otherwise. Additionally, we include the amount of the firm's write-off, $WRITEOFF_i$. Similarly to the previous regressions, we control for BM_i, $SynEarn_i$, and $SynRet_i$, which are defined the same way as in regressions (1) and (2).

To test our Hypothesis 5, which states that Followers' reversals of restructuring charges are associated with higher probability of meeting analysts' forecasts in the post write-off periods than that of Leaders, we estimate the following logistic regression:

$$\begin{aligned}\Pr(MBE_{i,N}) = F(&\kappa_0 + \kappa_1 Follower_i \\ &+ \kappa_2 Reversal_{i,N} + \kappa_3 Reversal_{i,N} * Follower_i + \kappa_4 WRITEOFF_i \\ &+ \kappa_5 INST_i + \kappa_6 RD_i + \kappa_7 LOSS_i + \kappa_8 Analyst_i + \kappa_9 |FE| \\ &+ \kappa_{10} Size_i + \kappa_{11} BM_i + \kappa_{12} SynEarn_i + \kappa_{13} SynRet_i + \vartheta_i)\end{aligned} \quad (5)$$

where dependent variable, $\Pr(MBE_{i,N})$, is the probability of meeting/beating analysts' forecast of annual earnings in the year *N* after the write-off. $MBE_{i,N}$ is a dummy variable that equals one if firm *i's* actual earnings reported in year *N* after the write-off are greater or equal to the latest outstanding consensus analysts' forecast before the earnings announcement, and zero otherwise. We consider two years after the write-off, and thus *N* takes the value of 1 or 2. We estimate regression (5) twice. First, on a full sample of firms with write-offs, and second on a sample of firms that would fail to meet the analysts' forecast based on pre-reversal earnings. The main explanatory variables are $Follower_i$, $Reversal_{i,N}$, and the interaction term between $Follower_i$ and $Reversal_{i,N}$. A positive coefficient on the interaction term between $Reversal_{i,N}$ and $Follower_i$ would indicate that Followers are more likely to meet analysts' forecasts when they reverse their restructuring charges. This would provide strong evidence of the strategic over-reporting of restructuring charges by Followers, who benefit from meeting earnings targets, which otherwise would not have been met.

We control for other variables that might impact managers' incentives and ability to meet analysts' earnings forecasts. Following Matsumoto (2002) we control for the institutional ownership ($INST_i$), reliance on implicit claims with other stakeholders, proxied by research and development intensity (RD_i), value relevance of earnings, proxied by the presence of losses prior to write-offs ($LOSS_i$), and growth prospects, proxied by the book-to-market ratio BM_i. We also control for the number of analysts following firm i ($Analyst_i$) and the uncertainty in forecasting

environment, proxied by the absolute forecast error ($|FE_i|$), which is the absolute value of the difference between reported earnings and the initial consensus forecast (measured as the first forecast each analyst made after the prior quarter earnings announcement), deflated by the stock price at the end of the last year before the write-off. $INST_i$, RD_i, $LOSS_i$, BM_i, and $Analyst_i$ are defined the same way as in regression (4). Additionally, we control for $WRITEOFF_i$, $Size_{i,t}$, $SynEarn_i$, and $SynRet_i$, which are defined in regressions (1) and (2).

5 Empirical Results

Herding

Table 4, Panel A provides an intuitive description of the write-off clustering by showing how soon Followers disclose a write-off after the most recent peer write-off. We observe that most Followers report write-offs within four months after the most recent write-off announcement coming from a peer firm (420 write-offs, or 91.50%). For example, the number of firms announcing write-offs in the same month as peers is 47 (10.24%), and the number of write-offs announced in the following month is 248 (54.03%). The number of firms reporting write-offs four months after the most recent peer write-off decreases substantially. For example, only seven firms report write-offs in the fifth month. This pattern of reporting is consistent with herding behavior. Importantly, Panel A does not show how soon Followers announce after Leaders, but rather provides a description that Followers' write-offs tend to happen together. Leaders' and Followers' write-offs are well separated in time because we use the absolute timing of the recession to define them.

Panel B presents the results of the Cox proportional hazard model. The estimation uses 1687 quarterly observations from 459 Followers. The coefficient estimate on $PEERWRITEOFF_i$

is positive and significant (0.02), indicating that the probability that a Follower, who has not previously reported write-offs, will report a write-off is positively associated with the number of peer write-offs in the preceding three months. The effect of $PEERWRITEOFF_i$ is also economically significant. The hazard ratio of 1.04 suggests that the probability that a Follower will report write-offs is 4% higher if the number of peers' recent write-offs increases by one.

The estimation results of the control variables are as follows. The coefficient estimate on RET_i is negative and significant, which suggests that the hazard of reporting a write-off has an inverse relation with the firm's cumulative abnormal return in the year prior to the quarter of observation. The hazard of reporting write-offs decreases with the product market share, as evidenced by negative coefficient on $MKTShare_i$. The coefficients on all other control variables are statistically insignificant.

Overall, the results of the duration analysis support Hypothesis 1, suggesting that a Follower's likelihood of reporting a write-off increases with the number of peer firms that have reported write-offs in the previous periods. This is consistent with the herding strategy, which predicts that Followers accelerate write-off reporting after observing Leaders, and might report write-offs even when they could further postpone such reporting.

Market Reaction

Table 5 reports estimation results of regression (2) that tests Hypothesis 2 regarding the asymmetric market reaction to Leaders' and Followers' write-offs. The coefficient estimate on $WRITEOFF_i$ is significantly negative (-0.154), indicating that overall the market reacts negatively to asset write-offs. However, a positive and statistically significant coefficient estimate (0.182) on the interaction of $WRITEOFF_i$ with $Follower_i$ indicates that Followers'

price responses to the write-off amount is less than that of the Leaders. Moreover, the sum of the coefficients on $WRITEOFF_i$ and $WRITEOFF_i * Follower_i$ is insignificantly different from zero, suggesting that the market does not react to Followers' write-offs.

Turning to the control variables, consistent with the prior literature, the price response coefficient on earnings surprise, *UE*, is positive and significant (0.29). The coefficient estimate on $SynRet_i$ is negative and significant (-0.028). The coefficient estimates on size, book-to-market ratio, $Follower_i$, and $SynEarn_i$ are insignificantly different from zero. Overall, the results in Table 5 support Hypothesis 2 that the market reacts less negatively to Followers' write-offs than to Leaders' write-offs.

Future Performance of Leaders and Followers after Write-Offs

Table 6 reports the results of regression (3), which tests empirical Hypotheses 2a and 2b regarding Leaders' and Followers' future operating performance after the write-off. In Model 1, the dependent variable is the change in a firm's industry-adjusted ROA over the two years following the write-off event ($ROA_{i,t,t+2}$). We find that after controlling for other factors associated with the future performance, Followers exhibit a greater increase in return on assets than Leaders, as evidenced by the positive and significant coefficient estimate on $Follower_i$, (0.024). The coefficient estimate on $WRITEOFF_{i,t}$ is negative and statistically significant (-0.517), while the coefficient estimate on the interaction term between $WRITEOFF_{i,t}$ and $Follower_i$ is significantly positive (0.191). A negative coefficient on $WRITEOFF_{i,t}$ indicates that Leaders' write-offs are negatively related to their future earnings. This is consistent with truthful write-off reporting because more severely affected by the economic shock firms have

larger write-offs and thus should have worse future performance.[18] However, a positive coefficient on the interaction term between $WRITEOFF_{i,t}$ and $Follower_i$ suggests the excessiveness of Followers' write-offs, because excessive write-offs shift future expenses into the current period, creating accounting reserves and allowing to boost future earnings performance when these reserves are released. Alternatively, a positive coefficient on the interaction term can suggest that Followers changed their business strategy and exhibit genuine improvement in their performance. However, if Followers' performance improvement is genuine and unrelated to the accrual expense shifting, their future cash flow performance should also improve. We test this alternative explanation in Model 2.

In Models 2, we use the change in a firm's industry-adjusted cash flows from operating activities ($CFO_{i,t,t+2}$) over the two years following the write-off event, scaled by the firm's total assets in the last fiscal year preceding the write-off, as dependent variables. In this specification, the coefficient estimates on $Follower_i$ and the interaction term between $WRITEOFF_{i,t}$ and $Follower_i$ are insignificantly different from zero, confirming our Hypothesis 3b that Followers and Leaders have the same performance with respect to operating cash flows. These findings refute the alternative explanation that the boost in Followers' future earnings is caused by their real actions and not by accrual expense shifting.

The coefficients on the control variables in Table 6 carry the expected signs. Significantly negative coefficients on the performance level in the year of the write-off, pre-write-off changes in the corresponding performance measures, and sales suggest that a firm's post-event performance is partially explained by its pre-event performance.

[18] For robustness, we also run the regression (3) using an industry-adjusted change in return on equity as a dependent variable, and obtained similar results.

In summary, the results reported in Table 6 confirm our empirical Hypotheses 3a and 3b. Faster improvement of future performance measured by GAAP bottom-line earnings of Followers, together with marginally similar performances measured by operating cash flows, provides circumstantial evidence that Followers strategically report excessive write-offs. Indeed, if a firm creates a reserve by transferring future expenses to write-offs, the release of this reserve would be reflected in ROA, as it includes all accrual accounting items, such as depreciation and amortization and other non-operating expenses, while leaving future cash flows unaffected.

Reversal of Restructuring Charges

In the previous sections, we provided circumstantial evidence, based on future performance, that Followers engage in strategic over-reporting of write-offs. While better future performance of Followers in terms of earnings (but not cash flows) suggests that Followers shift future expenses by overstating their write-offs, the possibility of an alternative explanation that Followers simply improve future performance because of their superior business strategy cannot be completely excluded. In this section, we provide direct evidence of the excessiveness of Followers write-offs by studying reversals of restructuring charges. If Followers excessively write-off their assets, they will reverse their restructuring charges in the future periods. Moreover, the reversals of restructuring charges will help them meet earnings benchmarks.

Panel A, Table 7 presents the univariate analysis of our hand collected sample of restructuring charges reversals. Out of 589 firms in our sample, we were able to obtain 10-K reports for 583, 576, and 554 firms for the first, second, and third fiscal years after the write-off quarter, respectively. We observe that Followers reverse restructuring charges more often than Leaders during the two fiscal years after the event. For example, 30.91% of the Followers

reverse restructuring charges in the first year after restructuring, while only 14.62% of the Leaders do so. In the second year, 30.20% of the Followers but only 21.71% of the Leaders reverse their restructuring charges. In the third year, 23.96% of the Followers reverse their restructuring charges and 17.46% of the Leaders do so. The difference between the frequencies of reversals is significantly different for the two fiscal years after the event, as evidenced by the results of the Chi-square test, but the difference between the frequencies in the third year is statistically insignificant.

Panel B presents results of logistic regression (4). The positive and statistically significant coefficient estimate on $Follower_i$ (0.55) demonstrates that even after controlling for other factors that can contribute to the decision and ability to reverse restructuring charges, Followers reverse restructuring charges more often than Leaders. The coefficient estimate on $Follower_i$ is also economically significant: the odds ratio of 2.13 suggests that the odds of reversing restructuring charges are 113% higher for Followers than that for Leaders.

As for the control variables, the coefficient estimate on pre-reversal earnings shortfall, $Shortfall_i$, is positive and statistically significant, which is consistent with prior literature finding that firm are more likely to reverse their restructuring charges when they are in danger of missing analysts' forecasts (Moehrle 2002). The size of the firm, which is often serves as a proxy of business complexity, and book-to-market ratio, which is a proxy for growth and ultimately business uncertainly, are also positively related to the probability of reversal. The number of analysts following the firm, $Analyst_i$, is negatively related to the frequency of reversals, suggesting that firms are more cautious in reversing restructuring charges if they face tighter investors' scrutiny. A significantly positive coefficient estimate on $WRITEOFF_i$ (0.44) suggests

that a larger write-off or restructuring charge amounts increases the likelihood of firms to reverse restructuring charges.[19]

In Table 8 we test our Hypothesis H5 that Followers meet analysts' earnings forecast more often when they reverse restructuring charges. Model 1 tests our baseline prediction that Followers are more likely than Leaders to meet/beat analysts' forecasts. The estimation uses all 1065 firm-year observations with available data for two fiscal years after the write-off. We report z-statistics based on the clustered by firm and year standard errors. Our results confirm that Followers are more likely than Leaders to meet/beat analysts' forecasts in the two fiscal years after write-offs, as evidenced by the positive and significant coefficient of 0.395 on $Follower_i$. This effect is also economically significant – the odds ratio of 1.48 indicates that the odds of meeting/beating analysts' forecasts are 48 percent higher for a Follower than for a Leader.

In Model 2 we further investigate whether reversals of restructuring charges indeed help Followers meet analysts' expectations when these benchmarks otherwise would not be met. We estimate Model 2 on the sample of 435 firm-year observations, which represents a subsample of the full sample used in Model 1 with an additional requirement that firms would fail to meet the analysts' forecast based on pre-reversal earnings. Similarly to Model 1, we report z-statistics based on clustered by firm and year standard errors. The insignificantly different from zero coefficient estimate on $Reversal_{i,N}$ indicates that Leaders are unable to meet analysts' expectations even when they reverse restructuring charges, suggesting that Leaders' reversals are more likely caused by managers' estimation errors. The coefficient estimate on the interaction term between $Reverse_{i,N}$ and $Follower_i$ is positive and significant (1.232), which

[19] Our untabulated analysis shows that approximately 75% of 589 firms in our sample report restructuring charges (76.92% of Leaders and 74.51% of Followers). The frequency of restructuring charges reported by Leaders and Followers is statistically the same. Thus, our results are not driven by the dominance of restructuring charges among Leaders or Followers.

provides evidence that when Followers reverse restructuring charges they are more likely to meet analysts' benchmarks than Leaders. The positive coefficient on the interaction term suggests that Followers are indeed more likely than Leaders to be involved in the strategic over-reporting of restructuring charges in the first place and subsequent reversals of these charges to meet earnings benchmarks.

The coefficient estimates for the control variables are largely consistent with prior literature. For example, the coefficient estimates on $Size_i$ is positive and significant, suggesting that larger firms are more likely to meet or exceed expectations (Matsumoto 2002). The negative coefficients on BM_i, and FE_i indicate that growth firms and firms with higher uncertainty in the forecasting environment are less likely to meet the forecasts.

Collectively, Table 8 provides direct compelling evidence that Followers strategically over-report write-offs to create accounting reserves and release them in the subsequent periods to meet the market expectations.

6 Summary and conclusion

In this paper, we demonstrate that bad news herding can be accompanied by over-reporting of bad news. Focusing on write-offs during two major recessions of 2001 and 2008, we document that firms *strategically* herd to report their write-offs following large write-offs reported by peer firms. Clustering of write-offs can be unsurprising given that economic shock affects almost all firms in the economy. However, the strategic nature of this clustered reporting is revealed by the excessiveness of write-offs (i.e., big bath strategy by clustered firms), which are subsequently partially reversed. We demonstrate this by using a hand-collected sample of reversals of restructuring charges. Our results reveal that reversals help herding firms meet analysts'

benchmarks that otherwise would not be met. While prior studies only imply that bad news herding is a beneficial strategy, we explain the mechanism behind the herding: we show that herding firms gain future benefits by initially over-reporting bad news, and later reporting better future performance by employing expense shifting.

Our study adds a multi-firm perspective to the big bath literature, extending the traditional standalone firm approach. We provide new empirical evidence that the big bath strategy can arise not only as a response to standalone firm-level events such as management's turnover or bad performance, but also as an optimal response to other firms' reporting choices. Although we focus on the strategic write-off herding behavior, our findings on the over-reporting of bad news can also be applied to other settings in which firms can strategically time their disclosures to herd with other firms, e.g., restatements, earnings warnings, and meeting various accounting benchmarks.

APPENDIX

In this Appendix, we explain how we collect the data set for the reversal of restructuring charges. First, for each firm in our write-off sample, we obtain 10-K reports from the Edgar reporting portal of the Securities and Exchange Commission for the three fiscal years after the write-off quarter by searching for firms' names and their CIK identifiers as reported in the COMPUSTAT database. Out of 589 firms in our sample, we were able to obtain 10-K reports for 583, 576, and 554 firms for the first, second, and third fiscal years, respectively, after the write-off quarter. Next, to identify whether a firm reversed its restructuring charges, we read sections of the "Notes to Financial Statements" in the 10-Ks that describe the reporting of restructuring activities. Firms' reporting practices for restructuring charge reversals vary considerably. Some firms state that they reversed the previously recorded accrual of restructuring charges (keywords "reversal" or "reversed"), while other firms report a negative non-cash adjustment to the restructuring charge accrual as a result of a change in accounting estimates or a reduction in the estimated costs (key words "adjustment", "non-cash adjustment", or "reduction"). The following table below provides five representative examples of firms' reporting practices. In Examples 1-3, firms explicitly stated that they reversed restructuring reserves that were no longer required. In Example 4, Payless Shoesource, Inc. reported a negative non-cash adjustment to its restructuring accrual in tabular form and stated in the table description that it incurred a non-recurring benefit as the result of lower than anticipated costs associated with the restructuring. In Example 5, E. I. Du Pont De Nemours and Company also did not use the words "reversal" or "reversed", but merely stated that it recorded a reduction in the estimated costs associated with the restructuring program.

Example 1: Excerpt from Notes to Financial Statement of **International Paper Company** for the fiscal year ended December 31, 2002
URL: https://www.sec.gov/Archives/edgar/data/51434/000095011703000884/a34643.txt
NOTE 6 SPECIAL ITEMS INCLUDING RESTRUCTURING AND BUSINESS IMPROVEMENT ACTIONS
Restructuring and Other Charges: 2002: During 2002, restructuring and other charges before taxes and minority interest of $695 million ($435 million after taxes and minority interest) were recorded. These charges included a $199 million charge before taxes and minority interest ($130 million after taxes and minority interest) for asset shutdowns of excess internal capacity and cost reduction actions, a $450 million pre-tax charge ($278 million after taxes) for additional exterior siding legal reserves discussed in Note 11, and a charge of $46 million before taxes and minority interest ($27 million after taxes and minority interest) for early debt retirement costs discussed in Note 13. In addition, a **$68 million pre-tax credit ($43 million after taxes) was recorded in 2002, including $45 million for the reversal of 2001 and 2000 reserves no longer required** and $23 million for the reversal of excess Champion purchase accounting reserves.
(Emphasis added)

Example 2: Excerpt from Notes to Financial Statement of **Axiom Corporation** for the fiscal year ended March 31, 2009
URL: https://www.sec.gov/Archives/edgar/data/733269/000073326909000013/f10k09.htm
2. RESTRUCTURING, IMPAIRMENT AND OTHER CHARGES (continued):
Spain Closure in fiscal 2007, the Company announced plans to shut down its operations in Spain. Upon the completion of this closure, the Company recorded $6.6 million of exit costs. **During fiscal 2008 the Company reversed $2.4 million of the accrual, offset by $0.8 million in currency translation expenses.** In fiscal 2009 $0.4 million in currency translation income was recorded. As of March 31, 2009, $0.5 million remained accrued for estimated data protection claims.
(Emphasis added)

Example 3: Excerpt from Notes to Financial Statement of **Genesco Inc.** for the fiscal year ended January 31, 2004

URL: https://www.sec.gov/Archives/edgar/data/18498/000095014404003909/g88468e10vk.htm

Note 2 Restructuring Charges and Discontinued Operations, Continued Nautica Footwear License Cancellation The Company ended its license to market footwear under the Nautica label, effective January 31, 2001. The Company's net sales for Fiscal 2002 included $6.1 million of sales of Nautica's branded footwear to fill existing customer orders and sell existing inventory.

During the second quarter of Fiscal 2002, the Company recorded **a restructuring gain of $0.3 million in connection with the successful completion of activities related to the Nautica Footwear license agreement's termination. The gain included a $0.1 million reversal of the earlier inventory write-down, because the Company was able to liquidate its Nautica Footwear inventories at better prices than it initially expected. The reversal is reflected in gross margin on the income statement.**

The Nautica footwear business contributed sales of approximately $6.1 million and an operating loss of $0.6 million in Fiscal 2002.

Restructuring Reserves

In thousands	Employee Related Costs	Facility Shutdown Costs	Other	Total
Balance February 2, 2002	$ 1,661	$ 2,504	$ 406	$ 4,571
Additional provision February 1, 2003	106	70	-0-	176
Charges and adjustments, net	(1,344)	354	(406)	(1,396)
Balance February 1, 2003	423	2,928	-0-	3,351
Excess provision August 2, 2003	(132)	(7)	-0-	(139)
Excess provision January 31, 2004	(22)	(1,779)	-0-	(1,801)
Charges and adjustments, net	(215)	(689)	-0-	(904)
Balance January 31, 2004 (included in other accrued liabilities)	**$ 54**	**$ 453**	**$ -0-**	**$ 507**

(Emphasis added)

Example 4: Excerpt from Notes to Financial Statement of **Payless Shoesource, Inc.** for the fiscal year ended January 31, 2004

URL:https://www.sec.gov/Archives/edgar/data/1060232/000095013704002667/c84303e10vk.htm\#111

The table below presents the activity of the $41.4 million reserve established as part of the 2001 non-recurring charge and the status of the reserve as of January 31, 2004. Costs were charged against the reserves as incurred. Reserves were reviewed for adequacy on a periodic basis and were adjusted as appropriate based on those reviews.

(dollars in millions)	Pre-tax 2001 Cash Charge	Cash Paid in 2001 and 2002	Adjustments in 2001 and 2002	Accrued as of Feb. 1, 2003	Cash Paid in 2003	Adjustments in 2003	Accrued as of Jan. 31, 2004
Store closing costs (including lease terminations, asset impairments, and employee termination costs)	$17.6	$ (8.5)	$(8.0)	$ 1.1	$(0.9)	$(0.2)	$ —
Division closing costs (including lease terminations, asset impairments, and employee termination costs)	3.3	(2.7)	1.8	2.4	(0.6)	(1.3)	0.5
Corporate employee termination costs	8.0	(8.0)	—	—	—	—	—
Professional fees required to design and implement the restructuring	6.4	(8.1)	2.0	0.3	—	(0.3)	—
Inventory liquidation costs (recorded as a component of cost of sales)	4.4	(2.4)	(2.0)	—	—	—	—
Other restructuring related costs	1.7	(3.1)	1.4	—	—	—	—
Total restructuring related costs	$41.4	$(32.8)	$(4.8)	$ 3.8	$(1.5)	$(1.8)	$ 0.5

We substantially completed our restructuring in 2002. **During 2003 we recorded a non-recurring benefit of $1.8 million as a result of lower than anticipated costs associated with the restructuring.** **During 2002, we recorded a net non-recurring benefit, resulting from lower than anticipated net costs associated with our restructuring recorded in 2001. In 2002, we recorded an additional charge of $2.0 million for professional fees and $1.4 million for relocation costs associated with implementing the restructuring that was announced during the fourth quarter of 2001.** These additional costs are reflected in the accompanying consolidated statement of earnings as non-recurring charges. **Also, during 2002, we decreased our reserve for store closings by $8.0 million, inventory liquidations by $2.0 million and increased our reserve for division closings by $1.8 million. This net**

reversal is reflected in the accompanying consolidated statement of earnings as non-recurring benefits.
(Emphasis added)

Example 5: Excerpt from Notes to Financial Statement of **E. I. DU PONT DE NEMOURS AND COMPANY** for the fiscal year ended December 31, 2010
URL:https://www.sec.gov/Archives/edgar/data/30554/000104746911000602/a2201761z10-k.htm
2008 Restructuring Program
During 2008, in response to the challenging economic environment, the company initiated a global restructuring program to reduce costs and improve profitability across its businesses. The program included the elimination of approximately 2,500 positions principally located in Western Europe and the U.S. primarily supporting the motor vehicle and construction markets. As a result, a charge of $535 was recorded in employee separation / asset related charges, net, which pertains to the cost of goods sold and other operating charges financial statement line item. This charge included $287 related to employee severance costs, $18 of other non-personnel charges, and $230 of asset related charges, including $111 for asset shut-downs and $119 for asset impairments.
The 2008 restructuring program charge of $535 reduced 2008 segment earnings as follows: Agriculture & Nutrition - $18; Electronics & Communications - $37; Performance Chemicals -$50; Performance Coatings - $209; Performance Materials - $94; Safety & Protection - $96; and Other - $31.
In 2009, the company recorded a **$100 net reduction in the estimated costs associated with the 2008 restructuring program.** This net reduction was primarily due to lower than estimated individual severance costs and workforce reductions through non-severance programs. The $100 net reduction impacted segment earnings for the year ended December 31, 2009 as follows: Agriculture & Nutrition - $1; Performance Chemicals - $3; Performance Coatings - $61; Performance Materials - $29; Safety & Protection - $2; and Other - $4.
In the fourth quarter 2010, the company recorded **a net reduction of $14 in the estimated costs associated with the 2008 restructuring program.** This net reduction was primarily due to lower than estimated individual severance costs and work force reductions through non-severance programs. The net reduction of $14 impacted segment earnings for the twelve months ended December 31, 2010 as follows: Performance Coatings - $10; and Performance Materials - $3; and Other - $1.
(Emphasis added)

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TABLE 1

Sample Selection

Data selection procedure	Excluded events	Remaining events
Select firm-quarter observations with (i) earnings announcements during the period starting 3 months before and ending 18 months after the beginning of the recessions of 2001 and 2008 (January 2001–September 2002 and September 2007–May 2009), (ii) negative pre-tax write-downs, restructuring charges, and goodwill impairment (sum of COMPUSTAT items WDP, RCP, and GDWLIP) greater than 1% of lagged total assets, and (iii) non-missing financial data required for analysis		1118
Exclude oil and gas, utilities, and financial and banking industries (codes 30, 31, 45, 46, 47, 48, and 49 of Fama-French (1993) industry classification)	79	1039
Retain only the first firm-quarter event per recession	345	694
Exclude industries that have fewer than three write-offs per recession	24	670
Exclude industries with no write-offs announced between 3 months before and 3 months after the beginning of the recession	81	589
Final write-off sample		**589**

TABLE 2
Frequency and amount of write-offs

Panel A: Frequency and amount of write-offs by industry-recession

Industry Name	All				Leaders				Followers			
	N	Mean	Median	Std dev	N	Mean	Median	Std dev	N	Mean	Median	Std dev
Recession 2001												
Recreation	3	0.021	0.020	0.009	2	0.025	0.025	0.006	1	0.012	0.012	.
Printing and Publishing	7	0.018	0.017	0.007	3	0.012	0.011	0.002	4	0.023	0.023	0.005
Consumer Goods	17	0.038	0.022	0.063	2	0.024	0.024	0.020	15	0.040	0.022	0.067
Apparel	9	0.030	0.016	0.030	1	0.012	0.012	.	8	0.032	0.020	0.031
Healthcare	4	0.023	0.022	0.015	1	0.037	0.037	.	3	0.018	0.010	0.014
Medical Equipment	5	0.044	0.033	0.037	1	0.048	0.048	.	4	0.044	0.026	0.042
Chemicals	11	0.025	0.023	0.015	2	0.020	0.020	0.004	9	0.026	0.025	0.017
Construction Materials	12	0.025	0.013	0.032	4	0.013	0.012	0.002	8	0.031	0.015	0.038
Steel Works	11	0.042	0.018	0.073	1	0.024	0.024	.	10	0.044	0.017	0.076
Machinery	11	0.019	0.016	0.008	1	0.016	0.016	.	10	0.019	0.018	0.008
Electrical Equipment	16	0.070	0.024	0.095	4	0.099	0.067	0.107	12	0.060	0.023	0.094
Automobiles and Trucks	6	0.049	0.042	0.035	2	0.063	0.063	0.074	4	0.041	0.042	0.007
Business Service	20	0.047	0.029	0.047	3	0.021	0.025	0.007	17	0.052	0.037	0.050
Computers	19	0.049	0.040	0.036	5	0.055	0.041	0.038	14	0.047	0.038	0.037
Computer Software	31	0.057	0.033	0.064	6	0.032	0.018	0.028	25	0.064	0.039	0.069
Electronic Equipment	47	0.097	0.029	0.243	5	0.373	0.063	0.685	42	0.064	0.028	0.100
Measuring and Control Equipment	7	0.024	0.019	0.014	2	0.027	0.027	0.019	5	0.023	0.019	0.014
Business Supplies	4	0.050	0.033	0.051	1	0.125	0.125	.	3	0.026	0.024	0.015
Transportation	5	0.083	0.060	0.084	1	0.060	0.060	.	4	0.089	0.066	0.096
Wholesale	20	0.047	0.029	0.054	4	0.047	0.042	0.024	16	0.047	0.024	0.060
Retail	16	0.036	0.024	0.032	6	0.029	0.014	0.038	10	0.040	0.032	0.029
Total recession 2001	281	0.052	0.024	0.111	57	0.068	0.024	0.210	224	0.048	0.024	0.066
Recession 2008												
Candy & Soda	4	0.075	0.035	0.094	1	0.036	0.036	.	3	0.088	0.034	0.111
Recreation	5	0.029	0.020	0.025	2	0.018	0.018	0.003	3	0.036	0.024	0.032
Consumer Goods	12	0.041	0.017	0.044	3	0.015	0.016	0.004	9	0.050	0.039	0.049
Apparel	7	0.029	0.032	0.010	1	0.036	0.036	.	6	0.028	0.028	0.010
Healthcare	4	0.131	0.110	0.109	1	0.025	0.025	.	3	0.166	0.139	0.102
Medical Equipment	6	0.060	0.015	0.112	2	0.015	0.015	0.007	4	0.082	0.015	0.137

Pharmaceutical Products	10	0.066	0.026	0.113	3	0.032	0.033	0.020	7	0.081	0.020	0.134
Chemicals	14	0.036	0.019	0.031	3	0.025	0.015	0.021	11	0.038	0.020	0.034
Textiles	4	0.087	0.087	0.058	1	0.016	0.016	.	3	0.111	0.088	0.041
Construction Materials	11	0.047	0.028	0.047	2	0.049	0.049	0.053	9	0.047	0.028	0.050
Steel Works	10	0.038	0.026	0.032	1	0.014	0.014	.	9	0.041	0.030	0.033
Electrical Equipment	10	0.096	0.068	0.083	2	0.112	0.112	0.027	8	0.093	0.040	0.093
Automobiles and Trucks	9	0.035	0.015	0.042	3	0.011	0.011	0.001	6	0.047	0.031	0.048
Communication	9	0.468	0.040	1.060	4	0.045	0.031	0.037	5	0.806	0.344	1.387
Personal Service	4	0.092	0.052	0.112	1	0.085	0.085	.	3	0.094	0.018	0.137
Business Service	36	0.080	0.037	0.100	7	0.039	0.037	0.028	29	0.089	0.036	0.109
Computers	15	0.092	0.040	0.106	4	0.027	0.020	0.022	11	0.116	0.059	0.116
Computer Software	21	0.071	0.021	0.096	5	0.034	0.019	0.040	16	0.082	0.042	0.106
Electronic Equipment	45	0.066	0.028	0.078	9	0.073	0.014	0.126	36	0.064	0.036	0.063
Business Supplies	7	0.044	0.043	0.021	3	0.034	0.031	0.024	4	0.052	0.055	0.019
Shipping Containers	5	0.042	0.018	0.057	2	0.019	0.019	0.003	3	0.058	0.018	0.075
Transportation	8	0.040	0.026	0.037	2	0.074	0.074	0.077	6	0.028	0.026	0.011
Wholesale	21	0.105	0.092	0.097	3	0.015	0.012	0.006	18	0.121	0.118	0.097
Retail	24	0.077	0.040	0.087	6	0.018	0.017	0.005	18	0.097	0.066	0.093
Restaurants, Hotels	7	0.038	0.022	0.040	2	0.030	0.030	0.011	5	0.041	0.015	0.049
Total recession 2008	308	0.078	0.030	0.200	73	0.038	0.020	0.052	235	0.091	0.040	0.226
Total	589	0.066	0.026	0.164	130	0.051	0.021	0.145	459	0.070	0.029	0.170

Panel B: Frequency of write-offs relative to the beginning of the recession (month 0)

Month relative to recession peak	Frequency of write-offs	Percent of write-offs	Cumulative frequency	Cumulative percent
-3	1	0.17	1	0.17
-2	21	3.57	22	3.74
-1	10	1.70	32	5.43
0	5	0.85	37	6.28
1	45	7.64	82	13.92
2	37	6.28	119	20.20
3	11	1.87	130	22.07
4	64	10.87	194	32.94
5	25	4.24	219	37.18
6	5	0.85	224	38.03
7	45	7.64	269	45.67
8	15	2.55	284	48.22
9	8	1.36	292	49.58
10	53	9.00	345	58.57
11	27	4.58	372	63.16
12	16	2.72	388	65.87
13	55	9.34	443	75.21
14	64	10.87	507	86.08
15	25	4.24	532	90.32
16	30	5.09	562	95.42
17	24	4.07	586	99.49
18	3	0.51	589	100

This table reports the frequency and amount of write-offs. Write-offs are defined as observations when the sum of negative pre-tax write-downs, restructuring charges, and goodwill impairment (sum of COMPUSTAT items WDP, RCP, and GDWLIP) greater than 1% of lagged total assets. Leaders are defined as firms having write-offs during the period starting 3 months before and ending 3 months after the beginning of the recession. Followers are defined as firms having write-offs during the period starting 3 months after the beginning of the recession and ending 18 months after the beginning of the recession. Industries are determined by the Fama-French (1993) 49-industry classification.
Panel A reports the frequency and amount of write-offs by industry-recession.
Panel B reports the frequency of write-offs relative to the beginning of the recessions.

TABLE 3
Descriptive statistics of write-offs sample

Variable	Leaders				Followers				Difference between Leaders and Followers			
	N	Mean	Med	Std. dev	N	Mean	Med	Std. dev	Mean		Med	
WRITEOFF	130	0.051	0.021	0.145	459	0.070	0.029	0.170	-0.019		-0.007	***
Size	130	7.492	7.185	1.806	459	7.171	6.977	1.635	0.321	*	0.208	**
BM	130	0.401	0.360	0.455	459	0.504	0.402	0.805	-0.103	*	-0.042	
Δ*BM*	130	-0.011	-0.005	0.112	459	-0.004	-0.006	0.155	-0.007		0.001	
ROA	130	0.046	0.053	0.129	459	0.051	0.053	0.118	-0.005		0.000	
Δ*ROA*	130	-0.006	-0.004	0.056	459	0.000	0.000	0.060	-0.006		-0.003	**
RET	130	-0.146	-0.113	0.451	459	-0.008	0.057	0.517	-0.138	**	-0.171	***
MKTShare	130	0.006	0.002	0.011	459	0.006	0.001	0.015	0.000		0.001	*
SynEarn	130	0.161	0.070	0.199	459	0.147	0.077	0.173	0.014		-0.007	
SynRet	130	0.255	0.243	0.159	459	0.383	0.380	0.209	-0.128	***	-0.138	***
Δ*MGMT*	130	0.169	0.000	0.376	459	0.133	0.000	0.340	0.036		0.000	
HIST	130	4.831	5.000	0.545	459	4.776	5.000	0.557	0.055		0.000	

This table presents the descriptive statistics of the write-off sample with 589 observations. Variable definitions: *WRITEOFF* is the sum of the write-downs, restructuring charges, and goodwill impairment (COMPUSTAT items WDP, RCP, and GDWLIP) deflated by the total assets at the end of the last fiscal year prior to the event quarter and converted to positive values. *Size* is the natural logarithm of a firm's average market value of equity in the four fiscal quarters before the write-off. *BM* is the book-to-market ratio measured at the end of the fiscal year prior to the write-off. *ΔBM* is the mean change in firm *i*'s book-to-market ratio over years -5 to -1. *ROA* is the return on assets of firm *i* in the fiscal year before the event, calculated as income before extraordinary items divided by lagged total assets (COMPUSTAT mnemonic: IB/(lag AT)). *ΔROA* is the mean change in firm *i*'s return on assets ratio over years -5 to -1. *RET* is the cumulative abnormal return of firm *i* computed over the year preceding the write-off. *MKTShare* is the ratio of a firm's total sales in the most recent fiscal year before the event quarter to the industry's total sales in that year. *SynEarn* is the R^2 of the regression of the firm's return on assets (ROA) on the industry ROA (calculated as the total industry earnings divided by the total industry assets) in the 20 quarters before the event quarter. *SynRet* is the R^2 of the regression of the firm's weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter. Δ*MGMT* is an indicator variable that equals one if the firm experiences a change in the top three executives in the fiscal year before or the fiscal year of the write-off and zero otherwise. *HIST* is equal to the number of significant write-offs that exceed one percent of the lagged firm total assets reported by the firm in the previous five years.

***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively, in a two-tailed test.

TABLE 4
Clustering of followers' write-offs

Panel A: Timing of Followers' write-offs relative to the most recent peer's write-off

Month	Frequency	Percent	Cumulative frequency	Cumulative percent
The same month	47	10.24	47	10.24
1	248	54.03	295	64.27
2	44	9.59	339	73.86
3	61	13.29	400	87.15
4	20	4.36	420	91.50
5	7	1.53	427	93.03
6	10	2.18	437	95.21
7	9	1.96	446	97.17
8	1	0.22	447	97.39
9	0	0.00	447	97.39
10	3	0.65	450	98.04
11	3	0.65	453	98.69
12	2	0.44	455	99.13
13	4	0.87	459	100

Panel B: Duration analysis of Followers' write-offs.

	Coefficient		z-stat	Hazard ratio
Peerwriteoff	0.02	**	4.58	1.04
UE	-0.03		1.60	1.02
Δ*Sale*	-0.01		0.18	1.03
RET	-0.12	***	8.49	1.22
Size	-0.01		0.11	1.03
MKTShare	-0.07	***	7.90	0.98
SynEarn	0.00		0.01	1.04
SynRet	0.02		0.14	1.10
Wald-test	29.50			
Number of Followers	1687			

Panel A reports how soon Followers issue their write-offs after the most recent peer's write-off. Panel B reports results for the Cox proportional hazard model:

$$h\,(t_i) = h_0(t_i)(a_0 + a_1 Peerwriteoff_i + a_2 UE_i + a_3 \Delta Sale_i + a_4 RET_i + a_5 Size_i + a_6 MKTshare_i + a_7 SynEarn_i + a_8 SynRet_i + e_i) \quad (1)$$

where the hazard rate, $h\,(t_i)$, is the probability density of a follower's reporting write-off on day t, given that it has not reported write-offs the preceding $t - 1$ days, $h_0(t_i)$ is the unspecified baseline hazard rate, being the same for all firms. Explanatory variables: $Peerwriteoff_i$ is the number of write-offs issued by industry peers in the three months preceding the earnings announcement of firm i. UE_i is the difference between the actual earnings and the latest outstanding analyst consensus forecast before the earnings announcement, deflated by the firm's stock price at the end of the last fiscal year prior to the event.

$\Delta Sale_i$ is firm i's sales growth in the write-off quarter from the same quarter in the previous year. RET_i is the cumulative abnormal return of firm i computed over the year preceding the write-off. $Size_i$ is the natural logarithm of firm i's average market value of equity in the four fiscal quarters before the write-off. $MKTshare_i$ is the ratio of firm i's total sales in the most recent fiscal year before the event quarter to the industry's total sales in that year. $SynEarn_i$ is the R^2 of the regression of the firms' return on assets (ROA) on the industry ROA (calculated as the total industry earnings divided by the total industry sales) in the 20 quarters before the event quarter. $SynRet_i$ is the R^2 of the regression of the firms' weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter. We rank UE_i, $\Delta Sale_i$, RET_i, $Size_i$, $MKTshare_i$, $SynEarn_i$, and $SynRet_i$ into deciles among all firms in the industry quarter that are covered by COMPUSTAT and CRSP. The industry classification is based on the Fama and French (1993) 49-industry classification. The regression is estimated on 1687 quarterly observations from 459 Followers.

***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively, in a two-tailed test.

TABLE 5
Stock price sensitivity to write-offs

Variable	Coefficient		z-stat
Intercept	-0.007		-0.76
UE	0.290	***	16.81
WRITEOFF	-0.154	*	-1.78
Follower	0.004		0.21
*WRITEOFF *Follower*	0.182	**	2.19
Size	0.002		0.69
BM	0.009		0.94
SynRet	-0.028	***	-2.23
SynEarn	-0.015		-0.45
N_obs	-0.007		-0.76
Adj R^2	2.37%		
F-test of $\gamma_1 + \gamma_3 = 0$: 38.08[a]			

This table presents the coefficient estimates of the OLS regression in the following form:

$$ANNRET_i = \gamma_0 + \gamma_1 WRITEOFF_i + \gamma_2 Follower_i + \gamma_3 WRITEOFF_i * Follower_i + \gamma_4 UE_i + \gamma_5 Size_i + \gamma_6 BM_i + \gamma_7 SynRet_i + \gamma_8 SynEarn_i + \tau_i \quad (2)$$

where $ANNRET_i$ is firm *i's* compound excess return over days 0 and +3 relative to the earnings announcement day, measured as the difference between the realized return and the corresponding size and book-to-market portfolio of the firm on the CRSP-COMPUSTAT universe obtained from Professor Kenneth R. French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. $WRITEOFF_i$ is the sum of the write-downs, restructuring charges, and goodwill impairment (COMPUSTAT items WDP, RCP, and GDWLIP), converted to positive values, and deflated by the total assets at the end of the last fiscal year prior to the event quarter. $Follower_i$ is an indicator variable that equals one if firm *i* is a Follower and zero otherwise. UE_i is the difference between the actual earnings and the latest outstanding analyst consensus forecast before the earnings announcement, deflated by the firm's stock price at the end of the last fiscal year prior to the event. $Size_i$ is the natural logarithm of the firm's average market value of equity in the four fiscal quarters before the write-off. BM_i is the book-to-market ratio measured at the end of the fiscal year prior to the write-off. $SynEarn_i$ is the R^2 of the regression of the firm's return on assets (ROA) on the industry ROA (calculated as the total industry earnings divided by the total industry sales) in the 20 quarters before the event quarter. $SynRet_i$ is the R^2 of the regression of the firms' weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter. We rank UE_i, $Size_i$, BM_i, $SynEarn_i$, and $SynRet_i$ into deciles among all firms in the industry quarter that are covered by COMPUSTAT and CRSP. $WRITEOFF_i$ is ranked among the firms reporting large write-offs. The z-statistics are based on bootstrapped standard errors clustered by recession.

***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively, in a two-tailed test.
[a] indicates statistical significance at the 1% level using an F-test.

TABLE 6
Future performance of Leaders and Followers

	Model 1: Dependent Variable industry-adjusted $\Delta ROA_{t,t+2}$			Model 2: Dependent Variable industry-adjusted $\Delta CFO_{t,t+2}$		
Variable	Coefficient		t-stat	Coefficient		t-stat
Intercept	-0.014		-0.50	-0.036		-1.29
Follower	0.024	**	2.11	0.016		1.47
WRITEOFF	-0.517	***	-3.19	-0.154		-0.99
*WRITEOFF*Follower*	0.191	*	1.91	-0.045		-0.48
$PERF_t$	-0.639	***	-15.04	-0.698	***	-16.53
$\Delta PERF_{t-1,t}$	-0.079		-1.56	-0.087	*	-2.01
ΔROA	-0.176	**	-2.21	-0.277	***	-4.09
ΔBM	0.026		0.53	0.067		1.39
$\Delta SALE_{t-1,t}$	0.002		0.14	-0.012		-0.94
INDGROWTH	-0.005		-0.44	0.021	*	1.78
FINLEV	-0.003		-1.61	-0.006	***	-2.89
SIZE	0.005		1.39	0.010	***	3.13
BM	-0.025	**	-2.50	-0.022	*	-2.28
MKTShare	0.149		0.47	-0.278		-0.90
ΔMGMT	-0.017		-1.43	-0.002		-0.20
SynEarn	-0.045	**	-1.95	0.009		0.40
SynRet	-0.015		-0.63	-0.052	**	-2.25
N_obs	556			556		
Adj R^2	38.51%			43.99%		

This table presents the regression coefficient of the following OLS regression:

$$\begin{aligned}\Delta PERF_{i,t,t+2} = {} & \gamma_0 + \gamma_1 Follower_i + \gamma_2 WRITEOFF_{i,t} + \gamma_3 WRITEOFF_{i,t} * Follower_i \\ & + \gamma_4 PERF_{i,t} + \gamma_5 \Delta PERF_{i,t-1,t} + \gamma_6 \Delta ROE_{i,t-5,t} + \gamma_7 \Delta BM_{i,t-5,t} \\ & + \gamma_8 \Delta SALE_{i,t-1,t} + +\gamma_9 INDGROWTH_{i,t-5,t} + \gamma_{10} FINLEV_{i,t-1} \\ & + \gamma_{110} SIZE_{i,t} + \gamma_{12} BM_{i,t} + \gamma_{13} MKTShare_{i,t-1} + \gamma_{14} \Delta MGMT_{i,t-1,t} \\ & + \gamma_{15} SynEarn_{i,t} + \gamma_{16} SynRet_{i,t} + \mu_i\end{aligned} \quad (3)$$

where the dependent variables, $\Delta PERF_{i,t,t+2}$, measure the change in the future performance of firm *i* from the event year *t* to two years after the event. Models 1 uses $\Delta ROA_{i,t,t+2}$ as a dependant variable, and Model 2 uses $\Delta CFO_{i,t,t+2}$ as a dependent variable. *ROA* is calculated as the ratio of income before extraordinary items (COMPUSTAT item IB) to the total assets (COMPUSTAT item AT). *CFO* is calculated as the ratio of cash from operations (COMPUSTAT item OANCF) to the total assets. All performance variables are adjusted by industry performance by subtracting the industry median of either ROA or CFO. $Follower_i$ is an indicator variable that equals one if firm *i* had write-offs that exceed 1% of total assets during the period starting 3 months before and ending 3 months after the beginning of the recession, and zero otherwise. $WRITEOFF_{i,t}$ is the sum of the write-downs, restructuring charges, and goodwill impairment (COMPUSTAT items WDP, RCP, and GDWLIP), converted to a positive amount, and deflated by the total assets at the end of the last fiscal year prior to the event quarter. $PERF_{i,t}$ takes the values of the industry-adjusted ROA or CFO in the event year in Models 1 and 2, respectively. $\Delta PERF_{i,t-1,t}$ is the change in these measures from one year before the event year to the event year. ΔROA_i is the mean change in firm *i*'s return on assets ratio over years -5 to -1. ΔBM_i is the mean change in the book-to-market ratio over years -5 to -1 prior to the event year. $\Delta SALE_{t-1,t}$ is the sales growth in the year prior to the event year. $INDGROWTH_{i,t-5,t}$ is computed as the mean change in aggregated industry sales over the five years prior to the event year. $FINLEV_{i,t-1}$ is the ratio of total assets (COMPUSTAT

item TA) to the book value (COMPUSTAT item CEQ) at the end of the last fiscal year prior to the event. $Size_i$ is the natural logarithm of the firm's average market value of equity in the four fiscal quarters before the write-off. $MKTshare_{i,t-1}$ is the ratio of the firm's total sales in the most recent fiscal year before the event quarter to the industry's total sales in that year. $\Delta MGMT_{i,t-1,t}$ is change in the top management, which is defined as an indicator variable that equals one if the firm experiences a change in the top three executives either in the write-off year or in the prior year. $SynEarn_{i,t}$ is the R^2 of the regression of the firm's return on assets (ROA) on the industry ROA (calculated as total industry earnings divided by total industry sales) in the 20 quarters before the event quarter. $SynRet_{i,t}$ is the R^2 of the regression of the firm's weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter.

***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively, in a two-tailed test.

TABLE 7
Reversals of Restructuring Charges

Panel A: Frequency of restructuring charges reversals

	Leader			Follower			Difference in frequency	
	Total	# reversed	% reversed	Total	# reversed	% reversed	Chi-stat	P-value
Year1	130	19	14.62	453	140	30.91	13.51	0.000
Year2	129	28	21.71	447	135	30.20	3.56	0.059
Year3	126	22	17.46	428	100	23.36	1.98	0.160

Panel B: Logistic regression of the reversals of restructuring charges

	Coefficient		z-stat	Odds ratio
Intercept	-0.05	***	1.93	
Follower	0.55	***	8.03	2.13
Shortfall	0.75	***	15.87	1.55
WRITEOFF	0.44	***	8.95	0.97
INST	-0.03		1.35	1.00
Analyst	0.00	***	0.00	0.91
RD	-0.09		7.13	1.04
LOSS	0.03		1.22	1.19
Size	0.17	***	0.42	1.39
BM	0.33	***	34.39	1.13
SynEarn	0.12		14.66	1.03
SynRet	0.03	*	1.18	0.95
N_obs	1069			
Reverse	296			
Did not Reverse	773			
Likelihood Ratio	68.89			
Wald	60.66			

Panel A reports the frequency of the reversals of restructuring. We hand collected the instances of reversals for three fiscal years after the event quarter from the 10-K reports available on the Edgar reporting portal of the Securities and Exchange Commission. Out of 589 firms in our sample, we located 10-K reports for 583, 576, and 554 firms for the first, second, and third fiscal years after the write-off quarter, respectively.

Panel B reports the results of the logistic regression modeling the probability of reversals of restructuring charges in the two years after a big write-off:

$$\begin{aligned}\Pr(Reverse_{i,N}) = F(&\mu_0 + \eta_1 Follower_i + \eta_2 Shortfall_i + \eta_3 WRITEOFF_i + \eta_4 INST_i \\ &+ \eta_5 Analyst_i + \eta_6 RD_i + \eta_7 LOSS_i + \eta_8 Size_i + \eta_9 BM_i \\ &+ \eta_{10} SynEarn_i + \eta_{11} SynRet_i + \xi_i)\end{aligned} \quad (4)$$

$Reverse_{i,N}$ is an indicator variable that equals one if firm *i* reverses restructuring charges in the year *N* after a write-off, and zero otherwise. *N* takes values 1 or 2. $Follower_i$ is an indicator variable that equals one if firm *i* had write-offs that exceed 1% of total assets during the period starting 3 months before and

ending 3 months after the beginning of the recession, and zero otherwise. $Shortfall_i$, is an indicator variable that equals one if a firm's pre-reversal earnings are below consensus analysts' forecasts and zero otherwise, where pre-reversal earnings are computed as actual earnings reported on IBES minus reversal amount multiplied by statutory tax rate of 40 percent. $WRITEOFF_i$ is the sum of the write-downs, restructuring charges, and goodwill impairment (COMPUSTAT items WDP, RCP, and GDWLIP) deflated by the total assets at the end of the last fiscal year prior to the event quarter, converted to a positive value. $INST_i$ is the percent of shares outstanding held by institutions. $Analyst_i$ is the number of analysts following the company. RD_i is the research and development expense (COMPUSTAT item XRD) divided by the total assets at the end of the fiscal year before the event. $LOSS_i$ is an indicator variable that equals one if firm *i* reports a negative income before extraordinary items (COMPUSTAT item IB) in the fiscal year before the write-off, and zero otherwise. $Size_i$ is the natural logarithm of the firm's average market value of equity in the four fiscal quarters before the write-off. BM_i is the book-to-market ratio measured at the end of the fiscal year prior to the write-off. $SynEarn_i$ is the R^2 of the regression of the firms' return on assets (ROA) on the industry ROA (calculated as the total industry earnings divided by the total industry sales) in the 20 quarters before the event quarter. $SynRet_i$ is the R^2 of the regression of the firms' weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter. We rank $INST_i$, $Analyst_i$, RD_i, $Size_i$, BM_i, $SynEarn_i$, and $SynRet_i$ into deciles among all firms in the industry-quarter that are covered by COMPUSTAT and CRSP. $WRITEOFF_i$ is ranked among the firms in our sample. z-statistics based on clustered by firm and year standard errors.

***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively, in a two-tailed test.

TABLE 8
Reversals of restructuring charges and meeting or beating analysts' expectations

	Model 1			Model 2		
	Coefficient	z-stat	Odds ratio	Coefficient	z-stat	Odds ratio
Intercept	0.417	0.66		-1.715 ***	3.88	
Follower	0.395 **	5.77	1.48	-0.284	0.79	0.75
Reversal				-0.430	0.57	0.65
*Reversal*Follower*				1.232 **	3.80	3.43
WRITEOFF	-0.025	0.71	0.98	0.039	0.70	1.04
INST	-0.030	1.07	0.97	0.007	0.02	1.01
RD	0.035	1.18	1.04	-0.021	0.17	0.98
LOSS	-0.070	0.08	0.93	-0.468	0.77	0.63
Analyst	-0.051	2.04	0.95	-0.062	1.07	0.94
|FE|	-0.132 ***	20.08	0.88	-0.193 ***	16.31	0.83
Size	0.181 ***	12.44	1.20	0.336 ***	12.59	1.40
BM	-0.075 **	5.66	0.93	-0.103 *	4.02	0.90
SynEarn	-0.002	0.01	1.00	0.045	1.07	1.05
SynRet	0.051	2.27	1.05	-0.020	0.10	0.98
Sample	Full sample			Firms that fail to meet analysts' forecasts based on pre-reversal earnings		
N_obs	1065			435		
Meet/Exceed	760			130		
Did not meet	305			305		
Likelihood Ratio	97.60			89.26		
Wald	88.30			66.48		

This table presents results from the logistic regression modeling the probability of meeting or beating the latest outstanding median consensus analyst forecast before the annual earnings announcement two years after a big write-off:

$$\Pr(MBE_{i,N}) = F(\kappa_0 + \kappa_1 Follower_i + \kappa_2 Reversal_{i,N} + \kappa_3 Reversal_{i,N} * Follower_i + \kappa_4 WRITEOFF_i + \kappa_5 INST_i + \kappa_6 RD_i + \kappa_7 LOSS_i + \kappa_8 Analyst_i + \kappa_9 |FE| + \kappa_{10} Size_i + \kappa_{11} BM_i + \kappa_{12} SynEarn_i + \kappa_{13} SynRet_i + \vartheta_i) \quad (5)$$

Model 1 is estimated on the 1065 firm-year observations, which is a full sample of firms with large write-offs and available consensus analysts' forecast during two fiscal years after a write-off.
Model 2 is estimated on the 435 firm-year observations, which is the sample of firms who would fail to meet analysts' earnings per share (EPS) forecasts based on pre-reversal earnings. Pre-reversal earnings are computed as actual earnings reported on IBES minus reversal amount multiplied by statutory tax rate of 40 percent. If a firm does not reverse restructuring charges, pre-reversal earnings are equal to actual reported earnings. Dependent variable is the probability of meeting/beating analysts' forecast of annual earnings in the year *N* after the write-off. *N* is equal 1 or 2. $Follower_i$ is an indicator variable that equals one if firm *i* had write-offs that exceed 1% of total assets during the period starting 3 months before and ending 3 months after the beginning of the recession, and zero otherwise. $WRITEOFF_i$ is the sum of the write-downs, restructuring charges, and goodwill impairment (COMPUSTAT items WDP, RCP, and GDWLIP) deflated by the total assets at the end of the last fiscal year prior to the event quarter, converted to a positive value. $INST_i$ is the percent of shares outstanding held by institutions. $Analyst_i$ is the number of analysts following the company. RD_i is the research and development expense (COMPUSTAT item XRD) divided by the total assets at the end of the fiscal year before the event. $|FE_i|$ is the absolute value

of the difference between reported earnings and the initial consensus forecast (measured as the first forecast after the prior quarter's earnings announcement), deflated by the stock price at the end of the last year before the write-off. $LOSS_i$ is an indicator variable that equals one if firm *i* reports a negative income before extraordinary items (COMPUSTAT item IB) in the fiscal year before the write-off, and zero otherwise. $Size_i$ is the natural logarithm of the firm's average market value of equity in the four fiscal quarters before the write-off. $SynEarn_i$ is the R^2 of the regression of the firms' return on assets (ROA) on the industry ROA (calculated as the total industry earnings divided by the total industry sales) in the 20 quarters before the event quarter. $SynRet_i$ is the R^2 of the regression of the firms' weekly stock returns on the value-weighted market returns and industry returns in the calendar year before the event quarter. We rank $INST_i$, $Analyst_i$, RD_i, $Size_i$, $SynEarn_i$, and $SynRet_i$ into deciles among all firms in the industry-quarter that are covered by COMPUSTAT and CRSP. $WRITEOFF_i$ is ranked among the firms in our sample. z-statistics based on clustered by firm and year standard errors. z-statistics based on clustered by firm and year standard errors.

***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively, in a two-tailed test.